How Collateral Affects Small Business Lending: The Role of Lender Specialization

by

Manasa Gopal
Georgia Institute of Technology

CES 21-22 **August 2021**

Abstract

I study the role of collateral on small business credit access in the aftermath of the 2008 financial crisis. I construct a novel, loan-level dataset covering all collateralized small business lending in Texas from 2002-2016 and link it to the U.S. Census of Establishments. Using textual analysis, I show that post-2008, lenders reduced credit supply to borrowers outside of the lender's collateral specialization. This result holds when comparing lending to the same borrower from different lenders, and when comparing lending by the same lender to different borrowers. A one standard deviation higher specialization in collateral increases lending to the same firm by 3.7%. Abstracting from general equilibrium effects, if firms switched to lenders with the highest specialization in their collateral, aggregate lending would increase by 14.8%. Furthermore, firms borrowing from lenders with greater specialization in the borrower's collateral see a larger growth in employment after 2008. Finally, I show that firms with collateral more frequently accepted by lenders in the economy find it easier to switch lenders. In sum, my paper shows that borrowing from specialized lenders increases access to credit and employment during a financial crisis.

* Scheller College of Business, Georgia Institute of Technology, manasa.gopal@scheller.gatech.edu. Any views expressed are those of the author and not those of the U.S. Census Bureau. The Census Bureau's Disclosure Review Board and Disclosure Avoidance Officers have reviewed this information product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2055 (CBDRB FY19-P2055-R1002, CBDRB-FY19-P2055-R1031, CBDRB-FY19-P2055-R1204).

I am grateful to Philipp Schnabl, Anthony Saunders, and Viral Acharya for extensive guidance and support. I would like to thank my discussant Allen Berger for thoughtful suggestions. I would also like to thank David Brown, Nicola Cetorelli, Adam Copeland, Mark Flannery, Abhinav Gupta, Arpit Gupta, Franz Hinzen, Sabrina Howell, Kose John, Theresa Kuchler, Simone Lenzu, Andres Liberman, David Lucca, Stephan Luck, Alan Moreira, Holger Mueller, Cecilia Parlatore, Fahad Saleh, Asani Sarkar, Alexi Savov, Johannes Stroebel, Greg Udell, James Vickery, Iris Yao, Nicholas Zarra, and seminar participants at University of Rochester (Simon), University of Florida (Warrington), Georgia Institute of Technology (Scheller), University of Houston (Bauer), Southern Methodist University (Cox), Federal Reserve Bank of New York, Indiana University (Kelley), Federal Reserve Board of Governors, Johns Hopkins University (Carey), Indian School of Business, Texas A&M Young Scholars Finance Consortium, and NYU Stern for comments. Part of this paper was completed during the Dissertation Internship at the Federal Reserve Bank of New York in the summer of 2019.

1 Introduction

Do credit supply shocks have heterogeneous effects across borrowers? In this paper, I focus on one aspect of a firm's balance sheet - collateral - to study how lenders alter their composition of borrowers when constrained. Collateral plays a central role in small business credit access, with over 88% of small business loans backed by collateral in 2016.[1] If lenders are differentially equipped to evaluate the collateral of a borrower, i.e., lenders have specialization by collateral type, then credit supply to the borrower may differ based on the lender's specialization. In this paper, I investigate the link between lender collateral specialization and small business outcomes in the aftermath of the 2008 financial crisis in the U.S.

To understand why collateral may affect lender behavior, consider the benefits and costs of collateral. On the one hand, collateral serves to reduce a lender's exposure to the borrower's default risk when providing credit. Collateral reduces lender loss by helping screen observationally identical borrowers, reducing moral hazard, and by allowing the lender to foreclose on the borrower's collateral in case of default.[2] On the other hand, the use of collateral is costly for lenders. They incur the cost of monitoring, screening, as well as disposing off collateral.[3] Differences in the benefits and costs of collateral may vary by collateral type and lender, driven by lender's expertise. These differences become consequential in a crisis. As capital becomes scarce and borrower default probabilities increase, the relative importance of collateral for credit access increases. If lenders have a comparative advantage (specialization) in evaluating certain categories of collateral and not others, it can affect the set of firms receiving credit. This, in turn, can have first order effects on real outcomes.

There are two main challenges in understanding how lender collateral specialization affects the allocation of credit. The first challenge is the lack of data on firm-level borrowing and firm collateral for small businesses in the United States. Studies on the financial crisis have largely focused on European markets or on large, syndicated loans in the U.S. due to the

[1] Loans below $1 million. Survey of Terms of Business Lending, Federal Reserve Board. Source - https://www.federalreserve.gov/releases/e2/201612/default.htm

[2] Collateral can serve as a signaling device reducing adverse selection (Stiglitz and Weiss (1981), Besanko and Thakor (1987a), Besanko and Thakor (1987b), Bester (1985), Bester (1987), and Chan and Thakor (1987)), moral hazard (Boot et al. (1991), Boot and Thakor (1994), and Holmstrom and Tirole (1997)), and by increasing contract enforceability (Albuquerque and Hopenhayn (2004) and Cooley et al. (2004))

[3] See Leeth and Scott (1989)

lack of detailed lending data for small businesses in the U.S. However, small businesses are the most likely to be affected by credit supply shocks. Nearly all small businesses in the U.S. are privately held and lack access to public capital markets. With fewer options to substitute credit, small businesses rely on debt for financing investment and growth. Thus, studies on large U.S. businesses or in regions with different banking and financial environments may underestimate the true effect of a financial crisis on the economy.[4]

I address this challenge by collecting a novel dataset covering all collateralized loans in Texas between 2002 and 2016. The matched borrower-lender loan data is collected from public records filed under the Uniform Commercial Code (UCC). I further link the loan-level data to the U.S. Census of Establishments for borrower outcomes. My paper is one of the first to create a quasi-credit registry for the U.S. using detailed information on borrower and lender collateral. As an added advantage, my dataset contains information on non-bank lenders such as finance companies who constitute nearly half of total small business lending in the U.S., but are often ignored in the academic literature. My final dataset contains around 486,000 loans to 93,000 firms from over 900 lenders between 2002 and 2016.

The second challenge in addressing my research question is the non-random matching between borrowers and lenders. The ideal experiment for understanding the effect of lender collateral specialization on credit supply would involve tracking credit to identical borrowers that were randomly matched ex-ante to lenders with varying levels of collateral specialization. However, it is unlikely in practice that borrowers and lenders match on random. Firms that borrow from lenders specialized in their collateral may be intrinsically different from firms that borrow from lenders with low collateral specialization. Any observed changes in lending, therefore, could be due to differences in borrower credit demand or changes in credit supply due to firm unobservables. Alternatively, lenders that are more specialized (lending only to borrowers whose collateral they have expertise in) may respond differentially when credit supply is constrained when compared to more diversified lenders. The key identification concern, therefore, is the ability to separate unobservable differences between borrowers and

[4]Small businesses are independently important, contributing nearly 50% of employment in the economy, and generating 2 out of the 3 net new private sector jobs. Source: Small Business Administration https://www.sba.gov/sites/default/files/advocacy/Frequently-Asked-Questions-Small-Business-2018.pdf

lenders from the effect of lender collateral specialization. Thus, for identification, I exploit variation in credit supply to the *same* firm for multi-relationship borrowers, as well as the variation across borrowers of the *same* lender.

To identify the impact of lender specialization on credit allocation, I use textual analysis to create a measure of *Firm-Lender Collateral Match Quality*. The goal of this measure is to capture the extent of specialization of a lender in the collateral of the borrower. The assumption underlying this measure is that lenders have greater expertise in the collateral that occurs more frequently in their loan portfolios, after accounting for the aggregate availability of that collateral in the economy.[5] Using loans originated between 2002 and 2007 (the pre-crisis period), each firm-lender pair is assigned a numerical value based on the (textual) similarity of the firm's collateral to the lending portfolio of its relationship lenders. This is a measure bounded between 0 and 1 with higher values indicating greater match quality. The goal of this paper is to identify whether differential firm-lender match quality on collateral affects the borrower's access to credit in the aftermath of the financial crisis.

My methodology is best understood with an example. Firm A borrows from two lenders - Frost National Bank and Financial Federal Credit Inc. The borrower pledges trucks to both these lenders. Approximately 4.5% of Frost National Bank's collateral portfolio consists of trucks while 34% of Financial Federal Credit's loans are made against trucks as collateral. The Firm-Lender Collateral Match Quality between Firm A and Financial Federal Credit will be higher than the match quality between Firm A and Frost National Bank. The focus of this paper is to explore whether credit supply to Firm A after 2008 varies between Financial Federal Credit and Frost National Bank due to differences in their collateral specialization.

To identify the causal effect of lender collateral specialization on credit supply, I focus on the sample of firm-lender pairs with a relationship in the pre-crisis (2002-07) period. I employ a *within*-firm and *within*-lender estimator to address concerns about unobserved differences in borrower and lender characteristics. I find that a one standard deviation increase in Firm-Lender Collateral Match Quality increases the probability of the *same* borrower receiving a new loan after the start of the crisis by 3.7%. This effect is economically

[5]Based on the theoretical literature (Winton (1999), Dell'Ariccia et al. (1999)) that suggests that lender's concentration in a sector implies expertise.

significant, equivalent to 17.9% of the unconditional probability that a firm gets a loan from its relationship lender. Under a partial equilibrium counter-factual exercise where borrowers match to lenders with the highest specialization in their collateral, aggregate lending would increase by 14.8%.

Next, I evaluate the potential sources of lender advantage driving the specialization of lenders in the aftermath of the financial crisis. My main focus is on the distinction between lending advantages that are *collateral-specific* from those that are industry-specific or firm-specific. While collateral specialization can be considered one aspect of industry specialization, I show that the effect of collateral match persists even after the inclusion of controls for lender specialization in an industry, and by looking across borrowers within the same lender-industry cell. I find that after controlling for lender specialization in the 6-digit NAICS industry of the borrower, a one standard deviation in Firm-Lender Collateral Match Quality increases the probability of receiving a new loan by 3.5%, roughly equal to the 3.7% increase in lending in the baseline specification.

I also test whether lending advantages are driven by specialization in collateral or firm-specific knowledge, such as soft information. Thus, I include proxies for borrower-lender relationship strength as controls in the baseline specification. While these measures may themselves be correlated to the collateral match between the borrower and the lender (i.e., stronger relationship because of expertise in collateral), I show that a one standard deviation increase in collateral match including relationship strength controls leads to a 2.1% higher likelihood of getting a new loan compared to 3.7% higher likelihood without the controls. As an alternate test for soft information, I study how firm-lender collateral match of *new* borrowers of the lender compare to its current set of borrowers. For new borrowers, the lender does not have private, firm-specific information. I show, however, that the new borrowers are closely related to the lender's collateral specialization. This provides further support to my contention that collateral specialization explains lender behavior, rejecting the null that collateral does not differentially affect credit supply across lenders.

In robustness tests, I show that lending behavior is not driven by the type of business the lender is involved in. Traditionally, banks are thought to do more cash-based lending (evaluate firms based on projected cash flows) while finance companies tend to lend against

collateral values. For some lenders in the sample, specifically captive finance companies, increasing collateral sales and collateral value may be the primary motivation for lending. I find that these differences do not explain the observed specialization patterns.

Alternatively, lenders may concentrate new lending to otherwise distressed borrowers to reduce the probability of having to recognize loan losses on old loans and thus, reduce charges against their loss reserves and capital. If the firm-lender collateral match captures the level of prior lending or commitments of the lender, they may be inclined to continue lending to borrowers with higher collateral match to prevent losses on their loan portfolio. I show, however, that low-capitalization banks, who are most likely to have such motives to distort lending,[6] do not behave differently from high-capitalization banks.

Next, I examine the impact of lender collateral specialization on firm-level access to credit and real economic activity. For the firm-level results, I create a measure of *Firm Collateral Match* as the weighted average of firm-lender collateral match qualities. I show that greater the aggregate measure of firm match quality, larger the availability of credit to firms from its relationship lenders. A one standard deviation increases in Firm Collateral Match leads to 3.2% increase in lending from relationship lenders, equivalent to 10.4% of the mean probability of a repeat loan to a firm.

Furthermore, I show that firm's match quality can have real implications affecting firm employment during the crisis, and the pace of recovery following the financial crisis. A one standard deviation increase in firm collateral match quality increases the average level of post-crisis firm employment by 0.83%. This effect is economically large. The average firm in the sample experiences a 6.6% growth in employment between the pre-crisis and post-crisis period. Thus, a one standard deviation increase in firm collateral match quality raises employment by a value equal to 12.5% of the average growth in employment.

The effect of firm's collateral match quality on employment implies that relationship lender matching is a significant determinant of firm outcomes. This suggests firms are unable to completely substitute for drop in lending from relationship lenders. To study the ability of firms to substitute, I once again focus on borrower collateral. I create a measure of *Firm Similarity* by comparing the collateral of the firm to the (weighted) average lender in the

[6]See Caballero et al. (2008)

economy. This measure quantifies how commonly accepted the borrower's collateral is in the economy. I show that firms with greater overall similarity (i.e. more lenders lending against the firm's collateral) are more likely to substitute to a new lender. A one standard deviation increase in firm similarity increases the probability of borrowing from a new lender by 3.4%.

In summary, this paper provides evidence on the important role of lender specialization in borrower collateral for firm outcomes in a downturn. I show that within-firm, and within-lender, a greater level of ex-ante collateral match between borrowers and lenders leads to increased credit supply in the aftermath of the financial crisis. This increase is due to lender specialization in collateral driven by informational advantage of the lender. I further show that quality of collateral match between the borrower and lender can have aggregate impact on total credit to the firm, as well as firm employment.

The rest of the paper is organized as follows. Section 2 documents how the paper relates to the extant literature. Section 3 described the data sources and panel construction. Section 4 describes the text analysis techniques used in creating the measure of Firm-Lender Collateral Match Quality. Section 5 describes the identification strategy and empirical results. Section 6 concludes.

2 Related Literature

This paper relates to several strands of the literature. First, my paper relates to the role of lender specialization in credit allocation. Traditional banking theory argues for diversification across projects (Diamond (1984), Boyd and Prescott (1986)). Here, diversification reduces risks associated with idiosyncratic shocks lowering monitoring costs for lenders. This suggests banks should avoiding concentrating their lending portfolio. However, the argument relies on banks having equal expertise in all sectors of the economy.[7] But, lender specialization has been shown to be valuable as it helps in information collection (Loutskina and Strahan (2011), Berger et al. (2017)), increase market valuations (Laeven and Levine (2007)), allows lenders to extract rents (Petersen and Rajan (1994), Rajan (1992)), and

[7]Diversification may hurt as monitoring becomes weaker in new sectors (Winton (1999), Acharya et al. (2006), Berger et al. (2010)) or if resource allocation across divisions is inefficient (Rajan et al. (2000)). Furthermore, Fricke and Roukny (2018) show that high leverage can undo the benefits of diversification

protects against market competition (Boot and Thakor (2000), Dell'Ariccia and Marquez (2004), Hauswald and Marquez (2006), Degryse and Ongena (2004)).[8]

Consequently, in practice, lenders tend to be specialized by type of borrower (Carey et al. (1998)), or export markets (Paravisini et al. (2018)) among other areas. Liberti et al. (2017) document the role of lender specialization in collateral. While Liberti et al. (2017) show that collateral can affect lending decisions of lenders in new markets, I show that the extent to which borrower's collateral matters for credit supply changes with lender constraints. Thus, I add to the literature on lender specialization by documenting the important role of collateral in lender specialization decisions when lenders are constrained, and the important real economic consequences of lender specialization on borrowers.

Second, my paper relates to the literature on matching between borrowers and lenders in the economy. Prior work has shown that borrower-lender matching is influenced by geographic proximity (Petersen and Rajan (1995), Petersen and Rajan (2002)), bank size (Stein (2002), Hubbard et al. (2002), Cole et al. (2004)), or bank capital structure (Schwert (2018)). I extend this literature by documenting matching based on collateral, and studying the consequences of matching for credit and real outcomes. In Schwert (2018), under the assumption that observed matches are optimal, the paper explores borrower-lender characteristics that explain the match. Unlike his approach, I estimate the quality of matches between borrowers and lenders and document the consequences of changes in match quality. I also examine how borrower-lender matching changes over the business cycle. In this respect, the mechanism is similar to the one described by Granja et al. (2018) for geographic proximity.

Third, my paper relates to the role of collateral in lending. Collateral is a significant feature of loan contracts, especially small business loans where over 88% of small business loans were backed by collateral in 2016. [9] On the theoretical side, collateral arises naturally in settings with asymmetric information.[10] The importance of collateral has also been

[8]Private information of some lenders may also have externalities on other market players. See for example, Stroebel (2016) or Murfin and Pratt (2019)

[9]Benmelech et al. (2019) document the secular downward trend in secured debt over the past century but do not focus on small business lending around the financial crisis.

[10]Collateral can serve as a signaling device reducing adverse selection (Stiglitz and Weiss (1981), Besanko and Thakor (1987a), Besanko and Thakor (1987b), Bester (1985), Bester (1987), and Chan and Thakor (1987)), moral hazard (Boot et al. (1991), Boot and Thakor (1994), and Holmstrom and Tirole (1997)), and by increasing contract enforceability (Albuquerque and Hopenhayn (2004) and Cooley et al. (2004)).

documented in the empirical literature.[11] Luck and Santos (2021) document how pledging different types of collateral affects the cost of borrowing. I add to the literature on the importance of collateral by showing that the benefits to collateral vary by the type of collateral as well as by lender. I also focus on the dynamic role of collateral in lending decisions.

Fourth, my paper relates to the literature on the role asset specificity in lending. Starting with seminal work by Shleifer and Vishny (1992), the literature has documented the important role of asset fire sales and asset redeployability for credit access. The empirical literature has shown that firms with liquid collateral receive loans with longer maturity (Benmelech (2008)), lower spreads on loans, higher credit ratings, and higher LTV ratios (Benmelech and Bergman (2009), Almeida and Campello (2007)), and have a lower cost of capital (Ortiz-Molina and Phillips (2014)). Asset redeployability has been shown to be an important determinant of leverage for small businesses (Campello and Giambona (2013), Giambona et al. (2018)) with special importance during periods of distress (Pulvino (1998), Schlingemann et al. (2002), Acharya et al. (2007)).[12] Consistent with this literature, I show using detailed firm-level data, and comparison across industries, that firms with more commonly accepted collateral have a easier time substituting credit when faced with a supply shock. However, I add to this literature by documenting not only the importance of the type of collateral but the importance of the lender lending against the collateral.

Finally, my paper relates to the literature on credit supply during and in the aftermath of the financial crisis. The literature argues that changes in credit supply played an important role in triggering and amplifying the financial crisis.[13] Ivashina and Scharfstein (2010) document the drop in bank lending to large businesses following the bankruptcy of Lehman Brothers. Chen et al. (2017), Bord et al. (2018), and Gopal and Schnabl (2020) document

Collateral also arises in settings with costly state verification (as in Townsend (1979), Gale and Hellwig (1985), and Williamson (1986)), and to incentivize lender monitoring (Rajan and Winton (1995)).

[11] For reference, see Berger et al. (2011b), Jiménez and Saurina (2004), Berger and Udell (1995), John et al. (2003), Berger and Udell (1990), Brick and Palia (2007), Chakraborty and Hu (2006), Jiménez et al. (2006), Berger et al. (2011a), Berger et al. (2016).

[12] Shleifer and Vishny (2010) provide a full review of the fire sales literature. In contrast, Diamond et al. (2019) argue that high asset pledgeability could hurt firms in a downturn. Collateral usefulness also depends on creditor rights (Calomiris et al. (2017), Vig (2013), Campello and Larrain (2015)), and ability to repossess the asset (Eisfeldt and Rampini (2008), Benmelech and Bergman (2008)). Furthermore, type of collateral pledged varies by firm characteristics (Liberti and Sturgess (2014), Mello and Ruckes (2017)).

[13] Mian and Sufi (2009), Mian and Sufi (2018) argue that expansion in supply of mortgages was responsible for the boom and bust in housing markets, and the subsequent recession.

specifically the impact of the financial crisis on small business lending.[14] I add to this literature by documenting the heterogeneity in treatment across borrowers of the same lender. With detailed information on borrowers and lenders of small business loans, I document a new channel for the propagation of credit supply shocks to the economy.[15] Furthermore, I contribute to the literature documenting the real effects of credit supply shocks with detailed information linking small business lending to employment outcomes.[16]

3 Data and Summary Statistics

3.1 Data Sources

The insights in this paper come from combining two data sources- UCC filings for information on firm-lender relationships and the Census of Establishments for firm outcomes.

3.1.1 UCC-1 Filings

An important contribution of this paper is the construction of a new dataset on small business lending. My main dataset is sourced from state-level public records filed under the Uniform Commercial Code (UCC). The UCC is the set of laws that guide all commercial transactions in the U.S., such as sales, leases, and rentals. Article 9 of the UCC states that secured creditors have the right to make a public filing detailing their claim on borrower assets when originating a secured loan. In case of borrower default, these filings determine priority in bankruptcy proceedings. Secured lenders without an active UCC filing are considered unsecured creditors by law. For this reason, and due to the low cost of making UCC filings (typically $15-$25 for electronic filings), I believe my sample is representative of the universe of secured lending.

UCC filings under Article 9 are made to determine security interest in "personal-property".

[14] Cortés et al. (2018), Acharya et al. (2018a), Covas (2018) argue that post-crisis stress testing of large banks led to decrease in small business lending.

[15] Chaney et al. (2012), and Adelino et al. (2015) document the importance of collateral channel using real estate as collateral

[16] See Bernanke (1983), Peek and Rosengren (2000), Benmelech et al. (2016), Ashcraft (2005), Chodorow-Reich (2013), Greenstone et al. (2014), Bentolila et al. (2017)

Filings are made at the state-level at Secretary of State offices in the state of the borrower.[17] Real estate transactions, while governed by the UCC laws, require lenders to make filings at local county offices responsible for tracking that piece of land.[18] Furthermore, properties with titles, such as automobiles, boats, and airplanes, generally do not require state-level UCC filings for liens.[19] Any other collateral pledged by borrowers must be detailed through a state-level UCC filing.

One of the biggest strengths of the UCC data is that it allows for the creation of a "quasi" credit registry for the U.S. including data on loans originated by bank and non-bank lenders such as finance companies.[20] To the best of my knowledge, Edgerton (2012) is the only other paper that creates a similar registry from UCC filings for the U.S. by focusing on businesses in California over a six-year period. Murfin and Pratt (2019) use data on equipment financing sourced from UCC filings to study optimal pricing by captive finance companies. However, their paper only includes heavy equipment financing of firms in construction and agriculture. A subsequent paper by Gopal and Schnabl (2020) uses UCC data from all 50 states in the U.S. to document the growing role of nonbanks in small business lending. However, their work does not focus on detailed text descriptions of collateral accepted by lenders.
One shortcoming, however, of the UCC data is that we can only observe the extension of credit. Loan terms such as loan amount or pricing information are not reported.[21]

3.1.2 Texas Data

In this paper, I mainly focus on firms operating in Texas. To understand the role of firm-specific collateral on firm outcomes, I need detailed information on collateral pledged by firms. While this information is available at individual state offices, a bulk download of

[17] State of incorporation for registered businesses or headquarters for unincorporated businesses.

[18] Over 80% of loans to small and medium-size businesses are backed by non real-estate collateral - see Luck and Santos (2021)

[19] Recent court rulings have opened up debate on the need for UCC-1 filings on titled property. See for example - https://www.cscglobal.com/blog/court-finds-certificate-of-title-alone-not-sufficient-to-create-security-interest.
If the titled property is inventory meant for sale, a UCC filing is required.

[20] List of largest lenders in the sample available in Appendix A5

[21] Petersen and Rajan (1994) show that, based on a survey of small businesses, availability of credit is altered on quantities, rather than prices. More recently, DeYoung et al. (2015) show that decrease in credit to SMEs during the crisis was caused not by increased pricing of credit risk but rather by quantity rationing.

historical data is either unavailable or prohibitively expensive. California and Texas are two states that allow for the bulk download of UCC filings. However, the California data only goes back six years from the date of download (see Edgerton (2012) for details).

The Texas Secretary of State website allows for the download of historical data starting from 1966. However, I restrict my sample to filings made from 2002 onwards. The main reason for this choice is a July 2001 change to the laws governing where UCC filings are to be made. Before this date, a UCC filing was required in every state in which a firm maintained assets. After 2001, the filing location was changed to the state of incorporation for incorporated businesses or the location of the CEO's office for unincorporated firms with multiple offices.[22]

Thus, the final sample includes six years (2002-07) before the crisis, and a nine year crisis and recovery period (2008-16) with a total of 995,657 new loan originations in the period.

Collateral Information As described above, UCC filings are made for all non real-estate, non-titled personal property of borrowers. Figure A1 gives an example of a typical UCC filing. The filing includes information on the borrower (Best Dedicated LLC located in Kernersville, North Carolina), the lender (Webster Capital Finance Inc), the date of the filing (8/12/2014), and a description of the collateral (in this case, trailers) pledged.

There is large variation in the type of collateral pledged for loans, a fact which is going to be critical for my identification strategy. For example, collateral can vary from very specifically identified assets (as in the example above which identifies assets by their serial numbers) to blanket liens. Detailed examples are provided in Internet Appendix Section IA1.3.

Blanket liens occur commonly in collateral descriptions. A blanket lien is a lien that gives the lender rights to seize all assets of the borrower in case of default. As such, these statements contain generic descriptions of the collateral, such as "equipment", "inventory", "assets", and so on. Thus, blanket lien descriptions do not provide sufficient information about the exact assets of the borrower, which is crucial for my measure and identification strategy. Thus, I remove from the sample loans with blanket lien pledges. My sample retains

[22]Including data before 2002 might lead to repeat counting of the same loan to a business with multiple offices.

firms with real assets where an exact description of the asset is available.

3.1.3 Longitudinal Business Database

For real outcomes at the firm-level, I use information from the U.S. Census Bureau, specifically the Longitudinal Business Database (LBD). The LBD contains annual data (as of March 12) on establishment level employment, payroll, industry, location, and years of operation for the universe of non-farm employer firms in the U.S.

The LBD is the most comprehensive and accurate source of firm-level employment available in the U.S. and contains time-invariant establishment identifiers to track changes in outcomes over time. The database covers both single-establishment and multi-establishment firms. A firm-level identifier tracks the various establishments operated by a single legal entity.[23]

Finally, I aggregate the establishment-level data to the firm-level to track the effects of credit access on firm employment. The majority of the sample ($\sim$ 92%) is single-establishment firms. For firms with multiple establishments, I take the firm county (industry) as the county (industry) with the highest employment share of the firm.

3.2 Matching

To track the relation between firm credit and employment outcomes, I link the loan data from UCC filings to the LBD. With no common identifiers between the UCC Filings and the Census data, I use a fuzzy match based on firm names. To improve the accuracy of the matches, I focus on fuzzy name matching within a ZIP code, i.e., I look for the closest name match among all firms in the borrower's ZIP code. I use a combination of bigram string comparators to aid with the matching.[24] Through my matching algorithms, I am able to match roughly 52% of the total loans. The match rate over time is provided in Internet

[23]FIRMIDs are generated from Employer Identification Numbers (EIN) in tax forms. Thus, a firm is a set of establishments under the same tax filing unit. A single large firm may have multiple EIN numbers. This is less of a concern for small businesses.

[24]See COMPGED and SPEDIS functionality in SAS

Appendix Figure IA1.[25]

The final matched sample includes 93,000 non-FIRE (finance, insurance, real estate) firms and roughly 486,000 loans between 2002 and 2016. Comparison of the full Census data to the matched UCC lending - Census data is provided in Table A2. On average, the matched sample is larger (70 employees in matched sample vs. 25 employees in the average firm) and older (13.6 vs 10.6 years in operation).

In this matched sample, 44,500 firms have at least one loan between 2002 and 2007 (pre-crisis period). Of these, 23,500 firms have loans with real assets pledged as collateral. These 23,500 firms, therefore, constitute my baseline sample. Summary statistics on the baseline sample are provided in Panel A of Table 1. The average firm has operated for 12.73 years as of March 2007, with 14.12 employees in that year.

4 Collateral Match Quality

The goal of this paper is to identify whether differences in level of firm-lender collateral match affect firm access to credit in the event of a credit supply shock. Specifically, I study how specialization of a lender in the assets of the firm can affect firm outcomes. In this section, I formalize what I mean by collateral match and lender specialization and how I construct these measures.

In principle, I want to estimate the collateral that a lender is specialized in and measure how a borrower's collateral compares to the specialization of the lender. My measure relies on the theoretical literature (Winton (1999), Dell'Ariccia et al. (1999)) that suggests that lender's concentration in a sector implies expertise. In these models, because lenders have more interaction with borrowers in sectors in which they have a greater exposure, they are better informed about these sectors. Similarly, under my measure, borrowers with collateral more in line to what the lender traditionally accepts (controlling for aggregate availability

[25]There are multiple reasons for unmatched firms in the original sample. First, the LBD only contains employer firms (non-farm payroll employment excluding non-profit organizations). Thus, non-employer firms with outstanding loans cannot be matched to the LBD. Non-employer firms account for nearly 23 of the 28 million establishments in the U.S. In unreported results, I show that the lending results are robust to including the entire sample of firms. Second, firms operating under multiple names might generate low match scores. Third, firms that exit the sample before the start of the financial crisis are dropped. Further detail on the data cleaning and matching are provided in Internet Appendix IA1.

of the collateral in the economy), would imply a better match on collateral.

I create the measure of firm-lender collateral match by examining the textual similarity between the borrower's collateral and the collateral accepted by the lender. To create the measure, I translate the text descriptions into a numeric equivalent and compare two descriptions using the cosine similarity measure. I describe each of these steps in detail below.

4.1 Text to Numeric Conversion

First, I translate textual descriptions of collateral into a numerical format suitable for analysis. I start by aggregating the collateral description for each loan filing and cleaning collateral descriptions.[26] Next, I create a dictionary of all words in the universe of collateral descriptions. I manually inspect the list to retain words that describe the collateral while removing extraneous descriptive words.[27] To retain loans/firms with real assets, I create a dictionary of words for all real assets (equipment and machinery) from my sample, and retain descriptions with just these words. Internet Appendix IA2 contains the full list of words.

The words are then transformed into a matrix of features (in my case, collateral types) using a "bag of words" approach. Each description is represented as a vector where the ith component takes a value of one if the ith feature is present, and zero if not.[28] Vectors are adjusted by feature weights across documents, i.e., the inverse document frequency (IDF). The IDF captures how common a given word is in the overall sample of loans. Scaling by IDF prevents the overweighting of common terms. The idea behind IDF is to provide higher weights to words with more information. Collateral that occurs rarely provides greater information about a lender's specialization if present in it's portfolio. In my case, the weighting controls the aggregate availability of the collateral in the economy.

[26] I remove punctuation, special characters, extra spaces, and numbers (like serial numbers of equipment) from the description. Furthermore, I remove stop words (most common words that occur in the English language). Words are stemmed using the Porter Stemmer.

[27] For example, common words in collateral description include "proceeds", "limited", "including' which do not add additional information about the assets are removed.

[28] The baseline measure does not include weighting by term frequency (TF), i.e., the number of times a term appears in a given description. Collateral descriptions very often repeat terms to describe the claims on the same asset. Thus, weighting by TF could lead to over weighting firm assets. I ensure results are qualitatively similar when including the weighting.

To understand the importance of weighting in my case, consider the following hypothetical example. Lender A's portfolio consists of 10% loans against cattle and 10% loans against tractors. Overall in the economy, only 1% of loans are made against cattle while 20% of loans are made against tractors. Without the weighting, the collateral match between a borrower with tractor to Lender A would be identical to the collateral match between a borrower with cattle and Lender A. However, the disproportionate share of cattle in Lender A's portfolio compared to the economy implies Lender A has greater specialization in cattle than the average lender in the economy. The weighting captures this effect.

To formalize, for each word w in collateral description c in the universe of collateral descriptions C, I create

$$\text{TFIDF}_{cw} = TF_{cw} \times IDF_{Cw}$$

where TF_{cw} takes the value 1 if the firm has the type of collateral and 0 if it does not, and

$$\text{IDF}_{Cw} = \log \frac{N}{|c \in C : w \in c|}$$

which is the log of the total number of collateral descriptions scaled by the number of descriptions where the term w appears

4.2 Cosine Similarity

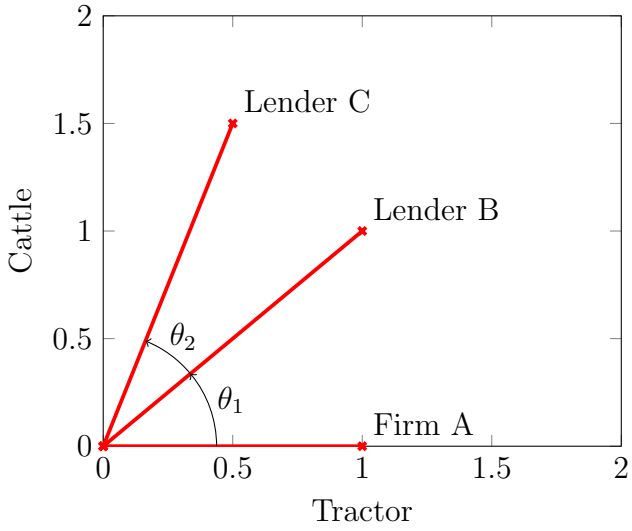
Next, I use the concept of cosine similarity to calculate the match quality on collateral between borrowers and lenders. Cosine similarity has been previously used in the finance literature to measure industry similarities in Hoberg and Phillips (2010) and Hoberg and Phillips (2016) and to calculate the impact of patents in Kelly et al. (2018). Technically, with each description represented in the vector space as described above, similarity between two descriptions can be calculated as the cosine of the angle between the two vectors. This commonly used measure follows from the Eucledian dot product formula

$$\text{Similarity} = cos(\theta) = \frac{\vec{A} \cdot \vec{B}}{\|\vec{A}\| \, \|\vec{B}\|}$$

To create my measure of collateral match between Firm A and Lender B, I compare the collateral of firm A to the collateral of the average borrower of lender B.

The intuition underlying cosine similarity is the idea that two collateral descriptions are similar if their vectors "point" in the same direction. It is a measure of orientation rather than magnitude. This is advantageous when comparing collateral descriptions of varying lengths. Descriptions with the same set of words in the same proportion will have similarity of one and descriptions with no common words between them will have a similarity of zero. In this aspect, cosine similarity performs better than standard measures such as Euclidean distance when high dimensional, sparse matrices are present.

To better understand the intuition, consider a simple example. Think of a universe with just two types of collateral - cattle and tractors - in equal proportion. In this world, every firm and lender can be represented in a two-dimensional space.



A firm with only tractors (Firm A) is on the X-axis. Lenders with both tractors and cattle can also be represented in the two-dimensional space. Consider two such lenders - Lender B (with 50% tractor and 50% cattle) and Lender C (25% tractors and 75% cattle). To measure the match quality (similarity) between a firm and lender, I calculate the cosine of the angle between the two vectors. The angle between Firm A and Lender B is smaller

than Firm A and Lender C. A smaller angle implies greater "similarity" in collateral, or in other words, a better match on collateral. In this example, Firm A has a better match to Lender B (cosine similarity of 0.7071) than it does to Lender C (cosine similarity of 0.3162).

I calculate the match quality at the firm-lender level as the cosine similarity between the firm and the average borrower of that lender in the sample. Measures are all calculated based on loans originated in the pre-period (2002-07). To construct the measure, I use information on real assets pledged by the borrower to its relationship lender, and compare that to the average borrower of its relationship lender.

Statistics on the firm-lender collateral match quality values are provided in Panel B of Table 1. The average match quality between firms and lenders on collateral for observed firm-lender pairs is 0.3827 with a standard deviation of 0.3085. The 10th percentile of the distribution is 0.01649 and 90th percentile is 0.8619.

5 Empirical Methodology and Results

5.1 Empirical Strategy

I study how collateral matching between borrowers and lenders affects credit supply to firms in the aftermath of the financial crisis. I am interested in understanding whether lenders treat borrowers differentially based on the collateral available at the firm and the level of matching between borrowers and lenders on collateral. Broadly speaking, a drop in credit to firms following the financial crisis could be driven either by lower firm demand, or a decrease in supply of credit to firms. Under the demand side explanation, firms that received fewer loans did so because they lowered their demand for credit. Under the supply side argument, lenders reduce credit to firms because of firm characteristics, or differences in firm collateral. I aim to isolate the credit supply channel, specifically the role of collateral, in determining firm credit access.

To estimate the causal effect of borrower-lender collateral match on credit supply, I follow a difference-in-difference strategy with continuous treatment intensity. I measure a firm's treatment intensity based on the level of matching between a borrower and lender using

collateral pledged by the firm to the lender in loans extended to it in the pre-crisis (2002-07) period. I then study the effect of the firm's collateral match to its lenders on credit access in the downturn.

5.2 Firm-Lender Level Results

I start by documenting the importance of collateral match for lending outcomes. First, I provide evidence for matching between borrowers and lenders based on collateral specialization of lenders. I show that the equilibrium distribution of borrower-lender pairs show a much higher collateral match score than would be implied by a random match.

Figure 1 plots two distributions. In the solid line, I plot the firm-lender collateral match scores for all possible firm-lender pairs. That is, for every firm in my sample, I create a measure of collateral match to every lender in the sample (irrespective of whether they actually borrow from them). To create the measure, I use the pre-crisis (2002-07) collateral pledged by the borrower and compare it to the pre-crisis lending portfolio of the lender. Note that the distribution is highly skewed with most of the distribution concentrated at near-zero values of collateral match.[29] In the dashed-line, I plot the same firm-lender collateral match scores for firm-lender pairs with at lease one loan in the pre-crisis period. We note that the observed firm-lender pairs is skewed to the right. Specifically, nearly half the observed firm-lender pairs are in the right 5% tail of the distribution of random scores. This provides suggestive evidence that collateral, and lender specialization in collateral is an important determinant of firm credit.

In this paper, I am interested in how the level of matching between firms and lenders affects lending during a crisis. For this, I focus my analysis on the second big takeaway from the plot, i.e. the heterogeneity in match scores across observed borrower-lender pairs. I exploit this heterogeneity to identify distribution of credit across borrowers in a downturn.

Figure 2 plots lending over time for firm-lender pairs with a relationship between 2002 and 2007. Firm-lender pairs are divided into two groups with above and below median scores on firm-lender match quality score. We see that lending to the two groups grow along similar

[29] Census disclosure rules require all distributions be capped at the 5th and 95th percentile.

paths in the pre-crisis period. After the start of the crisis, however, growth of loans between the two groups diverge. Firms with closer match to the lender see a smaller drop in lending during the crisis, and the gap between the two groups persists post-crisis.

However, as described above, this result is prone to endogeneity concerns. Firms that borrow from lenders that are specialized in their collateral may be inherently different from borrowers with weak lender matches. Similarly, lenders that lend to borrowers with collateral they have expertise in may respond differently when constrained from lenders with a diverse set of borrowers. Thus, I plot two additional figures. In Figure 3a, I split lenders to the same firm into above and below median match scores. That is, firm-lender pairs are classified as above or below median within firm. The sample here is restricted to firms with multiple relationships pre-crisis. As above, lending to the firm from the two groups of lenders grows on a similar path pre-crisis but diverges after the start of the crisis. Similarly, in Figure 3b, I separate firm-lender pairs into above and below median match quality within the same lender, i.e., borrowers with high vs. low match to a given lender. Observed lending patterns are similar with this categorization.

I now turn towards establishing this result more formally through regression analysis. My main empirical specification is as follows:

$$\text{Repeat Loan}_{fl} = \alpha_f + \gamma_l + \beta \text{Firm-Lender Collateral Match Quality}_{fl} + \epsilon_{fl} \qquad (1)$$

for every firm f, lender l with a pre-existing relationship in the pre-crisis period. The outcome variable takes value of 1 if the firm gets a new loan from the same lender in the post-crisis (2008-16) period. Since all firm-lender pairs have a loan between them ex-ante, repeat loan captures the change in lending to the firm. The main variable of interest is the measure of Firm-Lender Collateral Match Quality created based on pre-crisis (2002-07) loans. The measure captures the similarity between the borrower's collateral and the lender's collateral portfolio. The baseline specification also includes borrower and lender fixed effects to study the change in lending *within* the same firm across different lenders, as well as change in lending across borrowers of the *same* lender. Standard errors are clustered at the lender level.

Table 2 presents the results of the baseline specification in Equation 1. Column 1 presents the results for all firm-lender pairs observed in pre-crisis period. A one standard deviation increase in the match quality to lender increases the probability of a new loan by 2.04% equivalent to 10.3% of the mean probability of a repeat loan. In column 2, I include controls for county and industry[30] of the borrower to control for differences in demand. In Column 3, lender fixed effects are included to control for lender-level variation in specialization and lender level differences in borrower matching. After including lender fixed effects, local county-industry demand, and firm controls in column 4 we see a 2.53% increase in repeat loan probability for a one standard deviation increase in match quality.

In Columns 5-7, I restrict the sample to firms with multi-lending relationships in the pre-crisis period. Column 5 repeats the results of Column 3 for multi-lender relationship firms. In this, the effect is slightly larger for this sample with a one standard deviation increase in collateral match leading to a 3.36% increase in probability of a loan, equivalent to 16.2% of the unconditional probability of getting a repeat loan. In Column 6, I include firm fixed effects. Finally, Column 7 includes both firm and lender fixed effects. Including all controls, a one standard deviation increase in firm-lender collateral match quality increases the probability of the firm receiving a loan by 3.7%, or 17.85% of the mean and 9.13% of the standard deviation of the probability of receiving a repeat loan in the post-crisis (2008-16) period. These effects are large and economically important to small firms who rely on debt financing. This indicates the important role of borrower-lender collateral matching on small business lending.

Dynamic Difference-in-Difference

Next, I test for dynamic effects of firm-lender collateral match on lending. Specifically, I run the following panel regression:

$$\mathbf{y}_{flt} = \alpha_f + \gamma_l + \delta_t + \beta_t \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t + \epsilon_{flt} \tag{2}$$

where for each firm f, lender l pair with a loan in the pre-crisis period, I test for change

[30]For multi-establishment firms, county is the assigned based on the region with highest employment share for the firm. Industry at 2-digit NAICS level but robust to narrower industry definitions.

in lending each year t. The dependent variable is an indicator that takes value of one if the firm-lender pair is observed to have a loan in a given year, scaled by frequency of loans between the pair in the pre-crisis period. I scale the loans for a measure of percentage change in lending given the data limitation of only observing the extensive margin of loan originations. I am interested in how the coefficient on firm-lender collateral match changes over time.

The dynamic version of the difference-in-difference setting identifies the timing of the effect of firm-lender collateral match on loan outcomes, and to establish the existence of parallel pre-trends which is crucial for my identification strategy.

The results are presented in Figure 4.[31] I note that there are no statistically significant differences in lending across firms with different levels of firm-lender collateral match in the pre-crisis period. However, after the start of the financial crisis (2008-), firms with high quality match are more likely to get a loan. The effect persists for a number of years before recovering to pre-crisis levels in 2015. The magnitude of the effect is highest in 2009, with a one standard deviation increase in match leading to an 9.2% increase in lending.

5.2.1 Other Specialization Channels

Next, I aim to disentangle whether the observed results are truly driven by expertise in borrower collateral. Lenders could have borrower-specific advantages beyond expertise in collateral. Lenders could be specialized in the industry of the borrower, with an informational advantage over borrowers in certain industries versus others. Lenders could also have firm-specific knowledge, i.e., they may have borrower-specific information gathered through past relationships with the lender. Such expertise may help them distinguish good borrowers from bad, and could be the underlying mechanism driving observed lending behavior. I test for these alternate channels below.

Industry vs. Collateral Specialization

First, I test for lender specialization in the borrower's industry. Here, I analyze whether the observed lending patterns are driven by the collateral of the borrower or the industry of the

[31] Point coefficients can be found in Internet Appendix Table IA1

borrower. Clearly, collateral and industry specialization may overlap. Borrower collateral is largely driven by the industry in which the firm operates, for example - farmers often use tractors while restaurants do not. However, oftentimes, collateral could be more broad-based or more specific than implied by industry definitions. On the one hand, certain types of collateral are used across multiple industries (e.g. forklifts and trucks). On the other hand, lenders may specialize in lending only against certain types of collateral even within an industry. As an example, People's United Bank's equipment financing division makes loans against large service trucks but not against delivery or utility trucks.[32]

To separate lender specialization in an industry from its collateral specialization, I conduct two tests.

$$\text{Repeat Loan}_{fli} = \alpha_f + \gamma_l \times \delta_i + \beta \text{Firm-Lender Collateral Match Quality}_{fl} + \epsilon_{fl} \quad (3)$$

for firm f, in industry i, borrowing from lender l, I include lender times industry fixed effects to compare the treatment of borrowers within the same industry and who borrow from the same lender. The sample is once again firm-lender pairs with a pre-existing relationship in the pre-crisis period. The outcome variable takes value of 1 if the firm gets a new loan from the same lender in the post-crisis period.

Panel A of Table 3 presents these results. I present the results with 2-digit and 3-digit industry cells in Column 2 and 3 of Table 3. We see that including the industry interactions changes the magnitude of the effect on likelihood of a matched firm getting a repeat loan from the lender from 3.7% to 4.1% with 2-digit industry fixed effects and to 4.13% with 3-digit industry fixed effects. Collateral match, therefore, is still a significant determinant of credit to borrowers.

While we might be interested in more narrow industry specializations of lender, including very narrow industry fixed effects significantly would decrease sample size. Thus, in alternative tests, I include instead of lender-industry fixed effects, lender concentration by industry. I calculate lender concentration for narrow industry cells as the share of lending to that industry in the lender's portfolio.

[32] https://www.peoples.com/business/equipment-finance/peoples-united-equipment-finance-corporation/transportation

Panel B of Table 3 presents these results. I include lender concentration at the 2,4, or 6 digit NAICS level. On including lender shares in industry, the probability of receiving a repeat loan changes by 3.54% for a one standard deviation increase in firm-lender collateral match quality across the specifications. That is, industry specialization does not seem to explain away the observed borrower-lender collateral specialization.

Hard vs. Soft Information

Next, I test for whether lender behavior is driven by firm-specific knowledge. Lenders may collect firm-specific soft information through lending relationships. Changes in lending could, therefore, be driven by changes in firm-specific soft information rather than borrower collateral. To test this, I conduct two tests.

First, I include proxies for relationship strength as controls in my baseline regression. I create three proxies for strength of relationship - 1) Number of past loans from the lender, 2) share of total borrower lending from the lender, 3) time since the last loan between the borrower and lender and the start of the crisis. An increase in number of loans from the lender implies the lender has had greater interaction with the borrower, increasing the potential soft information the lender has about the borrower. Conversely, if a longer time has passed since the last loan to the borrower, the lender may have less up-to-date soft information about the borrower.

While these measures proxy for soft information, they may themselves be correlated with higher collateral match. For example, lenders may be willing to make a greater number of loans to borrowers whose collateral they are familiar with. Thus, adding these controls may bias downward the true effect of the importance of collateral matching. Consequently, the results shown in Table 4 are a conservative estimate for the effect of collateral match quality.

As shown in Table 4, including the controls for relationship lending decreases the magnitude on the coefficient of interest. In Column 1, I repeat the results from the baseline regression. Here, a one standard deviation increase in firm-lender match quality increases lending to the borrower by 3.72%. In Column 2, I use share of lending from the relationship lender as a control for relationship strength. Compared to the baseline regression, the effect here reduces to 2.29% increased loan likelihood, or 11% increase over the mean loan likeli-

hood. In Column 3, I include a measure of the average annual number of loans between the borrower and lender in the pre-crisis period. This decreases the effect to 10.1% above the unconditional mean of repeat loan . In Column 4, I include, as a control, the number of years since the last loan to the borrower. The effect of match quality in this case is equivalent to a 14.87% increase over the mean. Finally, I include both the number of loans and time from the last loan as a control. The final effect is a 2.1% increase in loan likelihood, or 10.1% over the mean value. Thus, even though the inclusion of these controls reduces the magnitude of the effect on collateral match quality, lender match is still an economically significant determinant of firm credit.

For the second test of importance of private firm-specific information, I test the importance of match on collateral for *new* borrowers of the lender. For firms with no prior-relationship, the lender does not possess private firm-specific information. As shown in Figure 5, the observed matches for borrowers with loans in the post-crisis period is significantly higher than would be implied by a random firm-lender pair match. This provides evidence for non-random matching between borrowers and lenders on collateral, conditional on the lender *not* having any borrower-specific private information. Thus, collateral is an important determinant of credit.

5.2.2 Robustness Tests

Next, I try understand the channels driving lender specialization in a downturn. Specifically, lenders could be specializing for multiple reasons. First, lender specialization may be driven by informational advantage. Lenders could have ex-ante private asymmetric information about the quality of collateral (ability to identify good collateral from bad), or possess greater ability to redeploy the collateral ex-post (which may include existing infrastructure for collateral storage and disposal, network of potential buyers etc.). Informational advantages may cause a lender to specialize in core collateral when in distress.

Second, lending behavior could be driven by the type of business the lender is involved in. Traditionally, banks are thought to do more cash-based lending (evaluate firms based on project cash flows) while finance companies lend against asset values (Carey et al. (1998)). For some lenders in the sample, for example captive finance companies, collateral sales

and value may be primary motivation for lending. In this case, one could be worried that concentration of lenders is driven by need to increase parent company sales and collateral value. Thus, observed behavior of change in lending against collateral could be driven by differences in underlying businesses.

Third, lenders may concentrate borrowing to prevent the writing down of bad loans, i.e. distressed firm lending (zombie lending in Caballero et al. (2008)). Distressed banks, i.e. banks with limited capital reserves and loan loss reserves, may reallocate credit to borrowers most likely to lead to loan losses if cut-off. If the firm-lender collateral measure captures the level of prior investment or commitment of the lender, they may be inclined to continue lending to borrowers with higher match to prevent losses on their portfolio.

In this paper, I argue that lender specialization is driven by informational advantage. While I cannot directly test for the amount of information about collateral available to the lender, I seek to eliminate the other potential channels described above.

Heterogeneity Across Lenders

First, I test for whether differences in underlying business of the lenders drive observed variation in lending. To test for variation across lenders, I include indicators for lender type in my baseline specification.

$$\begin{aligned}\text{Repeat Loan}_{fl} = \alpha_f + \gamma_l + \beta_1 &\text{Firm-Lender Collateral Match Quality}_{fl} \\ + \beta_2 &\text{Firm-Lender Collateral Match Quality}_{fl} \times \text{Lender Type}_l + \epsilon_{fl}\end{aligned} \tag{4}$$

Primarily, I test three main theories for specialization. First, I test for whether results are driven by the subset of lenders in my sample that are only concerned about collateral values. Lenders such as finance companies who lend primarily against collateral value of the borrower could be shifting focus in times of distress while traditional lenders such as banks lend to borrowers based on cash-flow evaluations. If that were the case, borrowers of finance companies would be affected while banks would not alter behavior based on collateral. In Column 1 of Table 5, I show that there is no statistically (or economically) significant difference between banks[33] and non-banks in their behavior in times of distress.

[33]Commercial banks, non-bank subsidiaries of bank holding companies, and credit unions.

Second, my results may be driven by lenders whose primary business is not small business lending. Specifically, captive finance companies, who are lending arms of manufacturing companies, may be interested in increasing asset sales and propping up collateral values to benefit the parent company sales in the goods market. These companies may increase lending to increase their parent company's revenue from sales. As these lenders are also on average more specialized, greater lending from better firm-lender collateral matches could be driven by increased lending from captive finance companies. I test whether this is case. However, it is important to note that captive finance companies also have informational advantage over other lenders in the economy. Specifically, captive finance companies have greater information about the true quality and resale value of the collateral due to their close association with the primary goods producer. Thus, difference across captive finance companies and other lenders could be driven by either channel. I check whether shift in lending is driven only be lenders whose primary goal is asset sales. In Column 2 of Table 5, I interact the firm-lender collateral match quality measure by an indicator for captive finance companies. The effect of increase in collateral match on lending is significantly higher for captive finance companies. A one standard deviation increase in match quality increases lending by 3.85% for non-captive lenders and 10.18% for captive lenders.

Third, I test for differences driven by large banks. As shown in Chen et al. (2017), the largest 4 commercial banks[34] pulled out of lending to small businesses in the aftermath of the financial crisis. If large banks are less specialized (more diversified) and pulled out of small business lending, the average continuing post-crisis firm-lender pair would appear to be better matched on collateral. I test for this in Column 3 of Table 5. There appears to be no statistically significant difference across Top4 banks and other lenders in the sample.

Distress Lending

Next, I test for the existence of distressed firm lending. In a downturn, lender decisions may be driven by bank need to prevent loan losses especially for undercapitalized banks. Such lenders, to prevent writing down bad loans, may continue making loans to bad borrowers. If firm-lender collateral match captures the extent of the lender's exposure to the borrower's

[34]JPMorgan Chase, Bank of America, Wells FArgo, Citibank after accounting for mergers and acquisitions

business, lenders have more to lose by cutting off lending to borrowers they are better matched to and they may be inclined to continue lending to such borrowers.

To test for presence of distressed lending, I compare lending behavior of banks based on their financial strength. Theories would indicate that distressed lending should be more pronounced for lenders who are capital constrained. Under-capitalized banks are more likely to engage in zombie lending behavior. Thus, I split my banks into above and below median capitalization based on Tier 1 Capital Ratio of banks as of December 2006. I test for differences across the two sets of banks through the following specification:

$$\begin{aligned}\mathbf{y}_{flt} =& \alpha_{fl} + \delta_t + \beta_{1t} \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t + \\ & \beta_{2t} \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t \times \text{Low Lender Capital}_l + \epsilon_{fci}\end{aligned} \tag{5}$$

where for each firm f, lender l pair with a loan in the pre-crisis period, I test for change in lending each year t. The dependent variable is an indicator that takes value of one if the firm-lender pair is observed to have a loan in a given year, scaled by frequency of loans between the pair in the pre-crisis period. I scale the loans for a measure of percentage change in lending given the data limitation of only observing extensive margin of loan originations. I am interested in the variation in the coefficient on firm-lender collateral match interacted with lender capitalization over time. Low Lender Capital takes a value of one if the lender has below median Tier-1 capital ratio as of December 2006.

Results are shown in Figure 6. I show that there is no statistically significant differences in specialization across lenders with high and low Tier 1 capital. The point coefficients, though insignificant, are negative, inconsistent with the distressed lending hypothesis. Coefficients are presented in Appendix Table **??**.

5.2.3 Counter-factual Exercise

I use the results from the within-firm regressions to study the aggregate effects of lender matching on loan supply. I follow a strategy similar to Chodorow-Reich (2013) and Acharya et al. (2018b) to estimate the aggregate effect on loan supply. For each borrower-lender pair, I estimate the counter-factual loan supply if the firm and lender were aligned on collateral.

Specifically, I estimate the additional credit to the firm if the lender had been specialized in the borrower's collateral.

I consider the effect of change in matching to a lender under two different conditions. First, I consider the highest possible firm-lender match score given the collateral the borrower pledged to the lender. In other words, for every firm-lender pair, I take as given the collateral pledged by the borrower to the lender. With this collateral, I compute the match scores to all other lenders in the sample and take the lender with the highest match score as the best match. Second, I consider improvement in lending under a hypothetical scenario where specialized lenders exist for all borrowers. That is, I take the highest value, the 95th and 90th percentile of the firm-lender collateral match score distribution. In this case, I estimate the increased lending to the borrower under the hypothetical scenario where a lender specialized to the same extent in the borrower's collateral is available.

I use a partial equilibrium analysis to determine the aggregate effect. Under the assumption that total lending is the sum of lending to individual firm-lender pairs, I can estimate the effect as follows:

$$\tilde{y}_{fl} = \hat{y}_{fl} + \beta \times [\tilde{\text{FLSim}}_{best} - \text{FLSim}_{fl}] \tag{6}$$

where $\hat{y}_{fl}$ denotes the fitted value from the regression in Equation 1. $\tilde{\text{FLSim}}_{best}$ is the counter-factual level of firm-lender similarity on collateral. In the baseline case, this value is 1 indicating perfect match in collateral between the borrower and lender. FLSim_{fl} is the observed value of the level of firm-lender collateral similarity. β_1 is the estimated coefficient in Table 2 Column 7.

$\tilde{y}_{fl}$ provides the estimate of loan supply conditional only on change in the level of firm-lender matching keeping all else equal.

The total lending in this counter-factual case is calculated by summing loan supply over all firm-lender pairs:

$$\sum \tilde{y}_{fl} \tag{7}$$

To estimate the gain from the shift in lender matching, I estimate the change in lending from the counter-factual lender matching scaled by the observed level of lending in the economy, or

$$\frac{\sum[\tilde{y}_{fl} - \hat{y}_{fl}]}{\hat{y}_{fl}} \tag{8}$$

The results are provided in Table 6. If borrowers changed their match to the most specialized lenders for their collateral, total lending to multi-relationship firms would increase by 14.76%. On the other hand, if there existed for each borrower, a lender as specialized in its collateral as the most specialized lender, the increase would be even higher. A shift in lender matching from the observed values to a counter-factual with perfect matching to the lender increases total lending by 42.67%. If the firm-lender pairs were instead at the 95th percentile of match score, lending would be 31.34% higher. At the lower bound of a match score at the 90th percentile, aggregate lending would still increase by 21.76%.

5.3 Firm-Level Results

Having established the importance of collateral for credit outcomes at the firm-lender level, I trace the impact of collateral match quality for firm outcomes. I create a measure of firm-level collateral match by computing the wighted average of firm-lender collateral match scores. That is,

$$\text{Firm Collateral Match}_f = \sum_{l \in L} \text{Lender Share}_{fl} \times \text{Firm-Lender Collateral Match}_{fl}$$

based on all relationship lenders l of the borrower f.

5.3.1 Lending

For firm credit outcomes, I first test the impact of firm collateral match on credit to firms from their relationship lenders. In Figure 7a, I plot lending over time to firms with above and below median match on collateral to their relationship lenders. We see that lending to the two sets of firms grows along a parallel path before the start of the crisis. After 2008, firms with better match to their relationship lenders get more credit from them, and this gap persists in the post crisis period.

To control for differences across borrowers with differential collateral match to their

relationship lenders, I regress firm credit from relationship lenders on the level of Firm Collateral Match, controlling for observable differences across borrowers

$$\text{Repeat Loan}_f = \alpha + \beta \text{Firm Collateral Match}_f + X_f + \epsilon_f \tag{9}$$

The results are provided in Panel A of Table 7. Columns 1-3 present the results for the full sample of firms in the sample. In Column 1, without any firm-level controls, a one standard deviation increase in firm collateral match increases lending from relationship lenders by 1.77%. Adding local county and industry fixed effects changes the magnitude of the effect to 2.05%. Finally, in Column 3, I include controls for firm size (log employment as of 2007) and age (log firm age as of 2007). This reduces the effect of firm collateral match to 1.55% for a one standard deviation increase in collateral match. This is equivalent to 5.08% of the mean likelihood of loan from at least one relationship lender.

In Columns 4-6, I focus on the set of firms with multiple pre-crisis lending relationships. This sample is a direct mapping to the set of firms in my baseline regression in Table 2. For this sample of firms, a one standard deviation increase in firm collateral match increases total lending from relationship lenders by 3.56%, double the size of the effect on the sample of all firms. Adding county, industry controls increases magnitude to 4.42%, and with inclusion of firm size and age controls, the final magnitude of the effect of a one standard deviation increase in collateral match is 3.19% increase in lending, equivalent to 10.35% of the mean and 6.91% of the standard deviation of mean probability of repeat lending to a firm.

Finally, To test the ability of firms to substitute, I again focus on the collateral of the firm. I create a measure of *Firm Similarity* which compares the collateral of the borrower to the collateral of the weighted average lender in the sample. This measure is analogous to the firm-lender collateral match quality created previously. The difference is that instead of comparing the borrower collateral to its relationship lenders, I now compare it to all lenders in the sample.

In Panel B of Table 7, I test borrower substitution to new lenders against the measure

of firm similarity.

$$\text{New Lender}_f = \alpha + \beta \text{Firm Similarity}_f + X_f + \epsilon_f \tag{10}$$

New Lender takes a value of 1 if the firm gets at least one loan after 2008 from a lender with no pre-crisis relationship.

Column 1 indicates that a one standard deviation increase in firm similarity increases the probability of shifting to a new lender by 4.36%. When I include county and 2-digit industry fixed effects, the effect becomes 4.52%. Including controls for firm size and age reduces the effect to 3.44% but still economically significant, equal to 6.56% of the mean probability of shifting to a new lender. In Columns 4-6, I present results by including the firm collateral match to relationship lenders. Better firm collateral match to relationship lenders reduces the probability of borrowing from a new lender by 1.9% in the strictest specification in Column 6.

5.3.2 Real Effects

In the previous section, I established that firm collateral match affects lending from relationship lenders. Next, I study the effect of firm collateral on real outcomes. I focus on firm employment in this paper.

In Fig 7b, analogous to credit, I plot firm employment against the two measures of firm collateral - Firm Collateral Match, which is the weighted average of firm-lender collateral match scores to the relationship lenders of the borrower. To create the figure, I scaled firm employment in a given year by the average level of employment at the firm in the pre-crisis period (2002-07) and average across all firms in the sample. Creating the average this way provides equal weights to small and large firms in my sample, which is important given the focus of this paper on small business outcomes. Notice the dispersion in employment growth across the two groups of Firm Collateral Match after the start of the crisis.

To study the effect of lender specialization in collateral on firm employment, I do the

following instrumental variable regression.

$$\begin{aligned} \text{Repeat Loan}_f &= \alpha + \gamma \text{ Firm Collateral Match}_f + X_f + \epsilon_{fci} \\ \Delta(\text{Employment})_f &= \alpha + \beta \hat{\text{Repeat Loan}}_f + X_f + \epsilon_{fci} \end{aligned} \tag{11}$$

for the sample of firms f with at least one loan in the pre-crisis period. New Loan takes value of 1 if the firm gets a new loan in the post-crisis period from any lender. I calculate change in employment as the change in average level of employment at the firm between the post-crisis and pre-crisis period as:

$$\Delta(\text{Employment})_f = \frac{\text{Employment}_{f,2008-16} - \text{Employment}_{f,2002-07}}{0.5 \times (\text{Employment}_{f,2008-16} + \text{Employment}_{f,2002-07})} \tag{12}$$

I use the above definition of employment to limit the influence of outliers. The growth rate definition in Equation 12 is a second-order approximation of the log difference growth rate around zero. It lies between [-2,2] and can accommodate exits, which is an important consideration for the sample of small businesses that I study.

Table 8 presents the results for employment. In Panel A, I present the OLS results. A one standard deviation increase in probability of receiving a loan from a relationship lender in the post-period increases employment at the firm by 7.28%. The IV results in Panel B are of similar magnitude at 8.64% growth in employment for one standard deviation increase in new loan. Results are robust to inclusion of county-industry fixed effects and firm controls.

5.4 Aggregate Patterns

The time series patterns for the set of borrowers receiving credit can provide more information on the importance of collateral. In this paper, I argue that the reduction in credit supply in the aftermath of the financial crisis was associated with a shift towards borrowers with a greater collateral match to their lenders. However, this analysis does not clarify how lender behavior varies at other points in time. I shed some light on changing lending behavior over time through two tests.

In Figure 8a, I plot the average level of firm-lender collateral match score for the set of

firms that receive credit in a give year. The main takeaway from the figure is that in the pre-crisis boom the average level of firm-lender collateral match is lower (and decreasing over time) than the average firm-lender similarity of the set of firms who receive credit in the post-crisis period. After 2007, the firm-lender collateral match is successively increasing till about 2012 after which it stabilizes. This suggests that the level of firm-collateral matching required for credit extension is most important in a downturn.

To identify whether this pattern is driven by just changing composition of lenders and borrowers in the sample, I run the following regression:

$$\text{Loan}_{flt} = \alpha_f + \gamma_l + \delta_t + \beta_t \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t + \epsilon_{flt} \tag{13}$$

for the set of all firms f and lenders l that receive a loan at any point in my sample. Loan takes a value of 1 if a firm-lender pair is observed with a loan in a given year t. Firm-lender collateral match is calculated based on the full sample (2002-16) of loans. I control for firm, lender, and time differences to test the time varying importance of firm-lender collateral match.

Figure 8b presents the results of the regression in Equation 13. Results are in line with the aggregate results presented - that is, firm-lender collateral match becomes important after the start of the financial crisis while the level does not differentially access to credit in the pre-crisis boom.

Consistent with these effects, Appendix Figure A4 presents changes in lender collateral portfolio over time. I plot the share of top 6 types of collateral in a lender's portfolio for every year between 2002 and 2016. These plots show that the share of the most common types of collateral in the lender's portfolio decrease in the pre-crisis boom, suggesting lenders expand in good times by lending against collateral outside their expertise. However, during the 2008 financial crisis and the years following it, the share of the most common types of collateral increases suggesting the lender's portfolio becomes more concentrated when they contract.

6 Conclusion

This paper documents the important role of collateral specialization of lenders for credit supply to borrowers in the aftermath of the financial crisis. Using novel loan-level data on all collateralized loans in Texas between 2002 and 2016 linked to the U.S. Census of establishments, I create a new measure of *Firm-Lender Collateral Match Quality* to quantify the extent of specialization of a lender in the collateral of the borrower.

By focusing on the set of borrower-lender pairs with pre-existing relationships before the start of the financial crisis, I show that a firm that was borrowing from lenders with greater specialization in its collateral is more likely to continue receiving credit after the start of the crisis. This effect is not driven by differences across firms or lenders but holds within borrowers of a lender and within lenders of a firm. Lender collateral specialization, in turn, affects firm-level outcomes such as employment.

On exploring the channels leading to lender specialization, I show that informational advantages in collateral are the most likely driver of lender specialization in a crisis. Furthermore, collateral specialization is distinct from other lender advantages that may be industry or firm-specific, such as lender concentration in an industry or the availability of firm-specific soft information.

The findings in this paper have important implications for heterogeneous effects of credit supply shocks. I show that the decrease in lending to borrowers of the same lender varies based on borrower collateral and its "match" to the lender's specialization by collateral. These findings also suggest that not all relationships are equally valuable to a borrower in times of a crisis, and credit substitution may be limited by lender collateral specialization.

References

Acharya, V., I. Hasan, and A. Saunders (2006): "Should Banks Be Diversified? Evidence from Individual Bank Loan Portfolios," *The Journal of Business*, 79, 1355–1412.

Acharya, V. V., A. N. Berger, and R. A. Roman (2018a): "Lending Implications of U.S. Bank Stress tests: Costs or Benefits?" *Journal of Financial Intermediation*, 34, 58 – 90.

Acharya, V. V., S. T. Bharath, and A. Srinivasan (2007): "Does Industry-Wide Distress Affect Defaulted Firms? Evidence From Creditor Recoveries," *Journal of Financial Economics*, 85, 787 – 821.

Acharya, V. V., T. Eisert, C. Eufinger, and C. Hirsch (2018b): "Real Effects of the Sovereign Debt Crisis in Europe: Evidence from Syndicated Loans," *The Review of Financial Studies*, 31, 2855–2896.

Adelino, M., A. Schoar, and F. Severino (2015): "House Prices, Collateral, and Self-Employment," *Journal of Financial Economics*, 117, 288 – 306.

Albuquerque, R. and H. A. Hopenhayn (2004): "Optimal Lending Contracts and Firm Dynamics," *The Review of Economic Studies*, 71, 285–315.

Almeida, H. and M. Campello (2007): "Financial Constraints, Asset Tangibility, and Corporate Investment," *The Review of Financial Studies*, 20, 1429–1460.

Ashcraft, A. B. (2005): "Are Banks Really Special? New Evidence from the FDIC-Induced Failure of Healthy Banks," *The American Economic Review*, 95, 1712–1730.

Benmelech, E. (2008): "Asset Salability and Debt Maturity: Evidence from Nineteenth-Centure American Railroads," *Review of Financial Studies*.

Benmelech, E. and N. Bergman (2008): "Liquidation Values and the Credibility of Financial Contract Renegotiation: Evidence from U.S. Airlines," *Quarterly Journal of Economics*.

——— (2009): "Collateral Pricing," *Journal of Financial Economics*.

Benmelech, E., N. Kumar, and R. Rajan (2019): "The Decline of Secured Debt," *Working Paper*.

Benmelech, E., R. R. Meisenzahl, and R. Ramcharan (2016): "The Real Effects of Liquidity During the Financial Crisis: Evidence from Automobiles," *The Quarterly Journal of Economics*, 132, 317–365.

Bentolila, S., M. Jansen, and G. Jiménez (2017): "When Credit Dries Up: Job Losses in the Great Recession," *Journal of the European Economic Association*, 16, 650–695.

Berger, A., S. Frame, and V. Ioannidou (2011a): "Tests of Ex Ante versus Ex Post Theories of Collateral Using Private and Public Information," *Journal of Financial Economics*.

Berger, A. N., M. A. Espinosa-Vega, W. S. Frame, and N. H. Miller (2011b): "Why do Borrowers Pledge Collateral? New Empirical Evidence on the Role of Asymmetric Information," *Journal of Financial Intermediation*, 20, 55 – 70.

Berger, A. N., W. S. Frame, and V. Ioannidou (2016): "Reexamining the Empirical Relation Between Loan Risk and Collateral: The Roles of Collateral Liquidity and Types," *Journal of Financial Intermediation*, 26, 28 – 46.

Berger, A. N., I. Hasan, and M. Zhou (2010): "The Effects of Focus versus Diversification on Bank Performance: Evidence from Chinese Banks," *Journal of Banking & Finance*, 34, 1417 – 1435, performance Measurement in the Financial Services Sector.

Berger, A. N. and G. F. Udell (1990): "Collateral, Loan Quality and Bank Risk," *Journal of Monetary Economics*, 25, 21 – 42.

——— (1995): "Relationship Lending and Lines of Credit in Small Firm Finance," *The Journal of Business*, 68, 351–381.

Berger, P. G., M. Minnis, and A. Sutherland (2017): "Commercial Lending Concentration and Bank Expertise: Evidence from Borrower Financial Statements," *Journal of Accounting and Economics*, 64, 253 – 277.

Bernanke, B. S. (1983): "Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression," *The American Economic Review*, 73, 257–276.

Besanko, D. and A. V. Thakor (1987a): "Collateral and Rationing: Sorting Equilibria in Monopolistic and Competitive Credit Markets," *International Economic Review*, 28, 671–689.

——— (1987b): "Competitive Equilibrium in the Credit Market Under Asymmetric Information." *Journal of Economic Theory*, 42, 167–182.

Bester, H. (1985): "Screening vs. Rationing in Credit Markets with Imperfect Information," *The American Economic Review*, 75, 850–855.

——— (1987): "The Role of Collateral in Credit Markets with Imperfect Information," *European Economic Review*, 31, 887 – 899, special Issue on Market Competition, Conflict and Collusion.

Boot, A. W. A. and A. V. Thakor (1994): "Moral Hazard and Secured Lending in an Infinitely Repeated Credit Market Game," *International Economic Review*, 35, 899–920.

——— (2000): "Can Relationship Banking Survive Competition?" *The Journal of Finance*, 55, 679–713.

Boot, A. W. A., A. V. Thakor, and G. F. Udell (1991): "Secured Lending and Default Risk: Equilibrium Analysis, Policy Implications and Empirical Results," *The Economic Journal*, 101, 458–472.

Bord, V., V. Ivashina, and R. Taliaferro (2018): "Large Banks and Small Firm Lending," *Working Paper*.

Boyd, J. H. and E. C. Prescott (1986): "Financial Intermediary-Coalitions," *Journal of Economic Theory*, 38, 211 – 232.

Brick, I. E. and D. Palia (2007): "Evidence of Jointness in the Terms of Relationship Lending," *Journal of Financial Intermediation*, 16, 452 – 476.

Caballero, R. J., T. Hoshi, and A. K. Kashyap (2008): "Zombie Lending and Depressed Restructuring in Japan," *American Economic Review*, 98, 1943–77.

Calomiris, C., M. Larrain, J. Liberti, and J. Sturgess (2017): "How Collateral Laws Shape Lending and Sectoral Activity," *Journal of Financial Economics*.

Campello, M. and E. Giambona (2013): "Real Assets and Capital Structure," *The Journal of Financial and Quantitative Analysis*, 48, 1333–1370.

Campello, M. and M. Larrain (2015): "Enlarging the Contracting Space: Collateral Menus, Access to Credit, and Economic Activity," *The Review of Financial Studies*, 29, 349–383.

Carey, M., M. Post, and S. A. Sharpe (1998): "Does Corporate Lending by Banks and Finance Companies Differ? Evidence on Specialization in Private Debt Contracting," *The Journal of Finance*, 53, 845–878.

Chakraborty, A. and C. X. Hu (2006): "Lending Relationships in Line-of-Credit and Nonline-of-Credit Loans: Evidence from Collateral use in Small Business," *Journal of Financial Intermediation*, 15, 86 – 107.

Chan, Y.-S. and A. V. Thakor (1987): "Collateral and Competitive Equilibria with Moral Hazard and Private Information," *The Journal of Finance*, 42, 345–363.

Chaney, T., D. Sraer, and D. Thesmar (2012): "The Collateral Channel: How Real Estate Shocks Affect Corporate Investment," *American Economic Review*, 102, 2381–2409.

Chen, B., S. Hanson, and J. Stein (2017): "The Decline of Big-Bank Lending to Small Business: Dynamic Impacts on Local Credit and Labor Markets," *Working Paper*.

Chodorow-Reich, G. (2013): "The Employment Effects of Credit Market Disruptions:

Firm-level Evidence from the 2008-9 Financial Crisis," *The Quarterly Journal of Economics*, 129, 1–59.

Cole, R. A., L. G. Goldberg, and L. J. White (2004): "Cookie Cutter vs. Character: The Micro Structure of Small Business Lending by Large and Small Banks," *The Journal of Financial and Quantitative Analysis*, 39, 227–251.

Cooley, T., R. Marimon, and V. Quadrini (2004): "Aggregate Consequences of Limited Contract Enforceability," *Journal of Political Economy*, 112, 817–847.

Cortés, K., Y. Demyanyk, L. Li, E. Loutskina, and P. Strahan (2018): "Stress Tests and Small Business Lending," *NBER Working Paper Series*.

Covas, F. (2018): "Capital Requirements in Supervisory Stress Tests and Their Adverse Impact on Small Business Lending," *TCH Working Paper*.

Degryse, H. and S. Ongena (2004): "The Impact of Competition on Bank Orientation and Specialization," *CEPR Discussion Papers 4543*.

Dell'Ariccia, G., E. Friedman, and R. Marquez (1999): "Adverse Selection as a Barrier to Entry in the Banking Industry," *The RAND Journal of Economics*, 30, 515–534.

Dell'Ariccia, G. and R. Marquez (2004): "Information and Bank Credit Allocation," *Journal of Financial Economics*, 72, 185 – 214.

DeYoung, R., A. Gron, G. Torna, and A. Winton (2015): "Risk Overhang and Loan Portfolio Decisions: Small Business Loan Supply before and during the Financial Crisis," *The Journal of Finance*, 70, 2451–2488.

Diamond, D. W. (1984): "Financial Intermediation and Delegated Monitoring," *The Review of Economic Studies*, 51, 393–414.

Diamond, D. W., Y. Hu, and R. G. Rajan (2019): "Pledgeability, Industry Liquidity, and Financing Cycles," *Journal of Finance*.

Edgerton, J. (2012): "Credit Supply and Business Investment During the Great Recession: Evidence from Public Records of Equipment Financing," *Working Paper*.

Eisfeldt, A. L. and A. A. Rampini (2008): "Leasing, Ability to Repossess, and Debt Capacity," *The Review of Financial Studies*, 22, 1621–1657.

Fricke, D. and T. Roukny (2018): "Generalists and Specialists in the Credit Market," *Journal of Banking & Finance*, 105335.

Gale, D. and M. Hellwig (1985): "Incentive-Compatible Debt Contracts: The One-Period Problem," *The Review of Economic Studies*, 52, 647–663.

Giambona, E., A. S. Mello, and T. J. Riddiough (2018): "Real Assets, Collateral and the Limits of Debt Capacity," *Real Estate Economics*, 46, 836–886.

Gopal, M. and P. Schnabl (2020): "The Rise of Finance Companies and FinTech Lenders in Small Business Lending," *Working Paper*.

Granja, J., C. Leuz, and R. Rajan (2018): "Going the Extra Mile: Distant Lending and Credit Cycles," Working Paper 25196, National Bureau of Economic Research.

Greenstone, M., A. Mas, and H.-L. Nguyen (2014): "Do Credit Market Shocks Affect the Real Economy? Quasi-Experimental Evidence from the Great Recession and 'Normal' Economic Times," *Working Paper*.

Hauswald, R. and R. Marquez (2006): "Competition and Strategic Information Acquisition in Credit Markets," *The Review of Financial Studies*, 19, 967–1000.

Hoberg, G. and G. Phillips (2010): "Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis," *The Review of Financial Studies*, 23, 3773–3811.

——— (2016): "Text-Based Network Industries and Endogenous Product Differentiation," *Journal of Political Economy*, 124, 1423–1465.

Holmstrom, B. and J. Tirole (1997): "Financial Intermediation, Loanable Funds, and the Real Sector," *The Quarterly Journal of Economics*, 112, 663–691.

Hubbard, R., K. Kuttner, and D. Palia (2002): "Are There Bank Effects in Borrowers' Costs of Funds? Evidence from a Matched Sample of Borrowers and Banks," *The Journal of Business*, 75, 559–581.

Ivashina, V. and D. Scharfstein (2010): "Bank Lending During the Financial Crisis of 2008," *Journal of Financial Economics*, 97, 319–338.

Jiménez, G., V. Salas, and J. Saurina (2006): "Determinants of Collateral," *Journal of Financial Economics*, 81, 255 – 281.

Jiménez, G. and J. Saurina (2004): "Collateral, Type of Lender and Relationship Banking as Determinants of Credit Risk," *Journal of Banking & Finance*, 28, 2191 – 2212.

John, K., A. Lynch, and M. Puri (2003): "Credit Ratings, Collateral, and Loan Characteristics: Implications for Yield," *The Journal of Business*, 76, 371–409.

Kelly, B. T., D. Papanikolaou, A. Seru, and M. Taddy (2018): "Measuring Technological Innovation over the Long Run," *Yale ICF Working Paper*.

Laeven, L. and R. Levine (2007): "Is there a Diversification Discount in Financial Conglomerates?" *Journal of Financial Economics*, 85, 331 – 367, the economics of conflicts

of interest financial institutions.

Leeth, J. D. and J. A. Scott (1989): "The Incidence of Secured Debt: Evidence from the Small Business Community," *The Journal of Financial and Quantitative Analysis*, 24, 379–394.

Liberti, J., J. Sturgess, and A. Sutherland (2017): "Information Sharing and Lender Specialization: Evidence from the U.S. Commercial Lending Market," *Working Paper*.

Liberti, J. M. and J. Sturgess (2014): "Uncovering Collateral Constraints," *Working Paper*.

Loutskina, E. and P. E. Strahan (2011): "Informed and Uninformed Investment in Housing: The Downside of Diversification," *The Review of Financial Studies*, 24, 1447–1480.

Luck, S. and J. Santos (2021): "The Valuation of Collateral in Bank Lending," *Working Paper*.

Mello, A. S. and M. Ruckes (2017): "Collateral in Corporate Financing," in *Working Paper*.

Mian, A. and A. Sufi (2009): "The Consequences of Mortgage Credit Expansion: Evidence from the US Mortgage Default Crisis," *The Quarterly Journal of Economics*, 124, 1449–1496.

——— (2018): "Credit Supply and Housing Speculation," *Working Paper*.

Murfin, J. and R. Pratt (2019): "Who Finances Durable Goods and Why It Matters: Captive Finance and the Coase Conjecture," *The Journal of Finance*, 74, 755–793.

Ortiz-Molina, H. and G. M. Phillips (2014): "Real Asset Illiquidity and the Cost of Capital," *Journal of Financial and Quantitative Analysis*, 49, 1–32.

Paravisini, D., V. Rappoport, and P. Schnabl (2018): "Specialization in Bank Lending: Evidence from Exporting Firms," *NBER Working Paper*.

Peek, J. and E. S. Rosengren (2000): "Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States," *American Economic Review*, 90, 30–45.

Petersen, M. A. and R. G. Rajan (1994): "The Benefits of Lending Relationships: Evidence from Small Business Data," *The Journal of Finance*, 49, 3–37.

——— (1995): "The Effect of Credit Market Competition on Lending Relationships," *The Quarterly Journal of Economics*, 110, 407–443.

——— (2002): "Does Distance Still Matter? The Information Revolution in Small Business Lending," *The Journal of Finance*, 57, 2533–2570.

Pulvino, T. C. (1998): "Do Asset Fire Sales Exist? An Empirical Investigation of Commercial Aircraft Transactions," *The Journal of Finance*, 53, 939–978.

Rajan, R., H. Servaes, and L. Zingales (2000): "The Cost of Diversity: The Diversification Discount and Inefficient Investment," *The Journal of Finance*, 55, 35–80.

Rajan, R. and A. Winton (1995): "Covenants and Collateral as Incentives to Monitor," *The Journal of Finance*, 50, 1113–1146.

Rajan, R. G. (1992): "Insiders and Outsiders: The Choice between Informed and Arm's-Length Debt," *The Journal of Finance*, 47, 1367–1400.

Schlingemann, F. P., R. M. Stulz, and R. A. Walkling (2002): "Divestitures and the Liquidity of the Market for Corporate Assets," *Journal of Financial Economics*, 64, 117 – 144.

Schwert, M. (2018): "Bank Capital and Lending Relationships," *The Journal of Finance*, 73, 787–830.

Shleifer, A. and R. W. Vishny (1992): "Liquidation Values and Debt Capacity: A Market Equilibrium Approach," *Journal of Finance*.

——— (2010): "Fire Sales in Finance and Macroeconomics," NBER Working Papers 16642, National Bureau of Economic Research, Inc.

Stein, J. C. (2002): "Information Production and Capital Allocation: Decentralized versus Hierarchical Firms," *Journal of Finance*, LVII, 1891–1921.

Stiglitz, J. and A. Weiss (1981): "Credit Rationing in Markets with Imperfect Information," *The*.

Stroebel, J. (2016): "Asymmetric Information about Collateral Values," *The Journal of Finance*, 71, 1071–1112.

Townsend, R. M. (1979): "Optimal Contracts and Competitive Markets with Costly State Verification," *Journal of Economic Theory*, 21, 265 – 293.

Vig, V. (2013): "Access to Collateral and Corporate Debt Structure: Evidence from a Natural Experiment," *The Journal of Finance*, 68, 881–928.

Williamson, S. D. (1986): "Costly Monitoring, Financial Intermediation, and Equilibrium Credit Rationing," *Journal of Monetary Economics*, 18, 159 – 179.

Winton, A. (1999): "Don't Put All Your Eggs in One Basket? Diversification and Specialization in Lending," *Manuscript, University of Minnesota*.

Figures

Figure 1: Distribution of Firm-Lender Collateral Match Quality

This figure plots the kernel density for Firm-Lender Collateral Match Quality. Unit of observation is a firm-lender pair. Firm-Lender Collateral Match Quality captures the level of collateral specialization of the lender in the borrower's collateral. Values are capped at 5th and 95th percentiles. The solid line includes all potential firm-lender pairs based on the total set of borrowers and lenders in Texas. The dashed line plots the firm-lender collateral match scores for equilibrium observed firm-lender matches with at least one loan between the pair in the pre-crisis (2002-07) period.

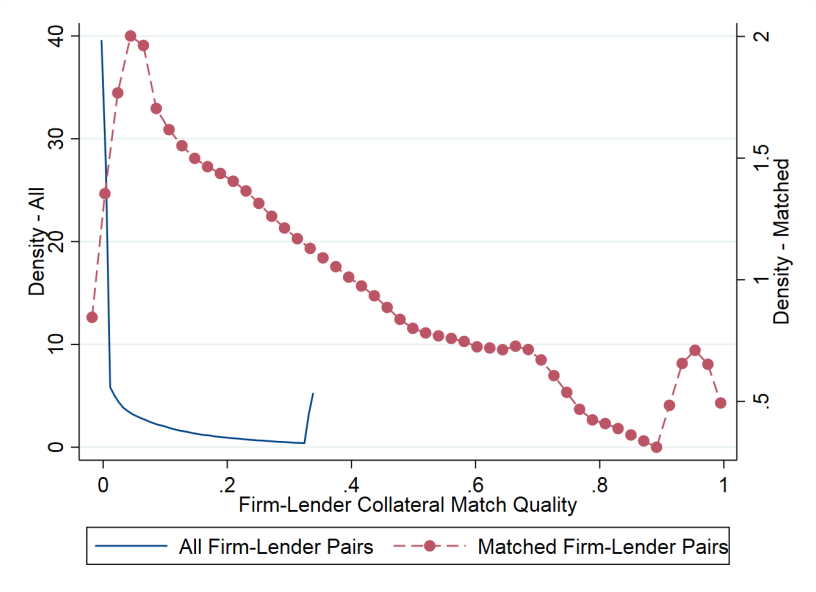


Figure 2: Effect of Firm-Lender Collateral Match on Lending

This figure plots new loan originations between 2002 and 2016 to study the effect of borrower-lender collateral match on access to credit around the 2008 financial crisis. The sample consists of borrower-lender pairs with a lending relationship between 2002-07. On the Y-axis, log of the number of loans originated in a given year demeaned by the average pre-crisis (2002-07) log number of loans is plotted. Borrower-lender pairs are classified into above and below median *Firm-Lender Collateral Match Quality*. Firm-Lender Collateral Match Quality captures the level of collateral specialization of the lender in the borrower's collateral. It is created by comparing the collateral pledged by the borrower to collateral portfolio of the lender based on pre-crisis (2002-07) loans. Higher values of the measure implies the lender has a greater specialziation in the collateral of the borrower.

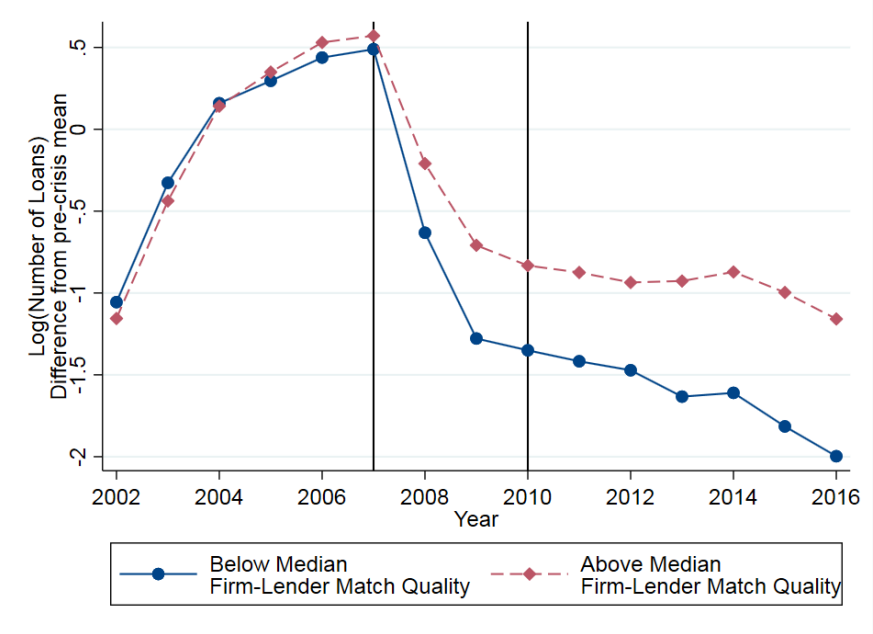
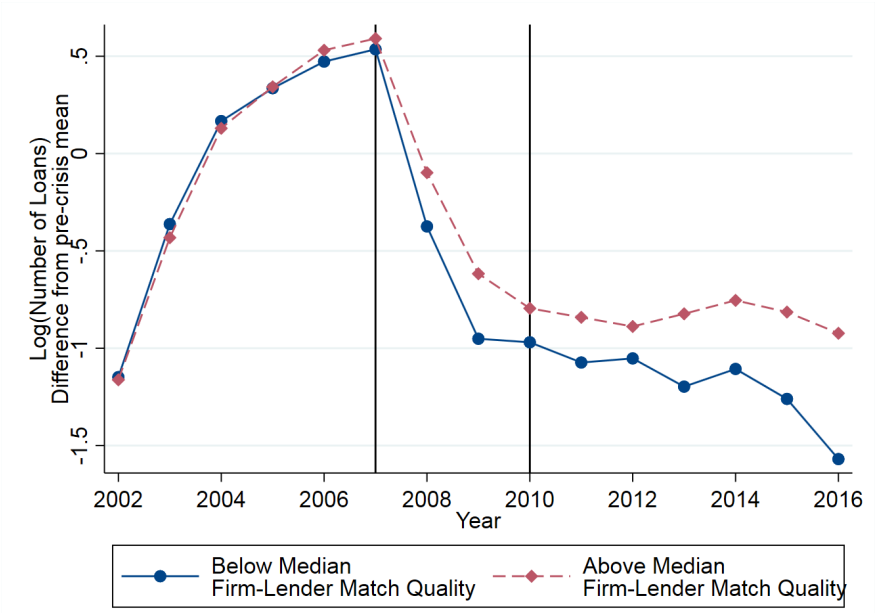


Figure 3: Effect of Firm-Lender Collateral Match on Lending - Within Group

This figure plots new loan originations between 2002 and 2016 to study the effect of borrower-lender collateral match on access to credit around the 2008 financial crisis. The sample consists of borrower-lender pairs in Texas with a lending relationship between 2002-07. Firm-Lender Collateral Match Quality captures the level of collateral specialization of the lender in the borrower's collateral.

(a) **Within Firm**

Within each firm, lenders with pre-crisis relationship are classified into above and below median collateral match quality. The sample is restricted to firms with multiple lending relationships.



(b) **Within Lender**

Within each lender, firms that borrowed at least once between 2002-07 are categorized into above and below median collateral match quality.

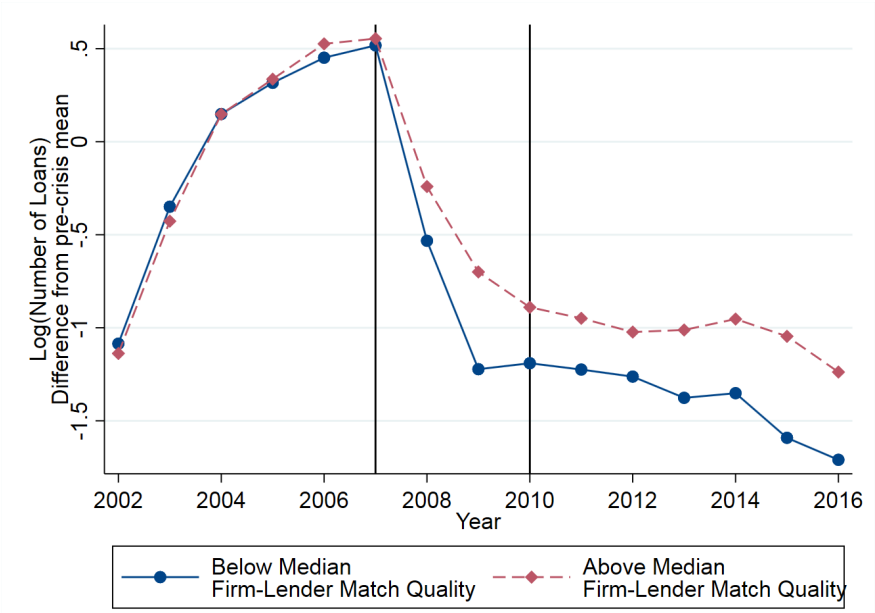


Figure 4: Time Varying Effect of Firm-Lender Collateral Match on Lending

This figure examines the time-varying effect of borrower-lender collateral match on access to credit around the 2008 financial crisis. The sample consists of borrower-lender pairs in Texas with a lending relationship between 2002-07. Observations are at the firm-lender-year level. Regression betas from the following specification are plotted:

$$\mathbf{y}_{flt} = \alpha_{fl} + \gamma_{lt} + \beta_t \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t + \epsilon_{flt}$$

for firm f, lender l, and year t. The dependent variable is an indicator that takes value of one if the firm-lender pair is observed to have a loan in a given year, scaled by frequency of loans between the pair in the pre-crisis period. Firm-Lender Collateral Match Quality captures the level of collateral specialization of the lender in the borrower's collateral, and is measured based on pre-crisis (2002-07) loans between the borrower and lender. Regression includes firm-lender (α_{fl}) and lender-year (γ_{lt}) fixed effects. $\mathbf{1}_t$ takes value 1 in year t and is zero otherwise. Standard errors are clustered at the lender level. Point coefficients and 95% confidence intervals are plotted. Coefficients can be found in column 4 of Table IA1.

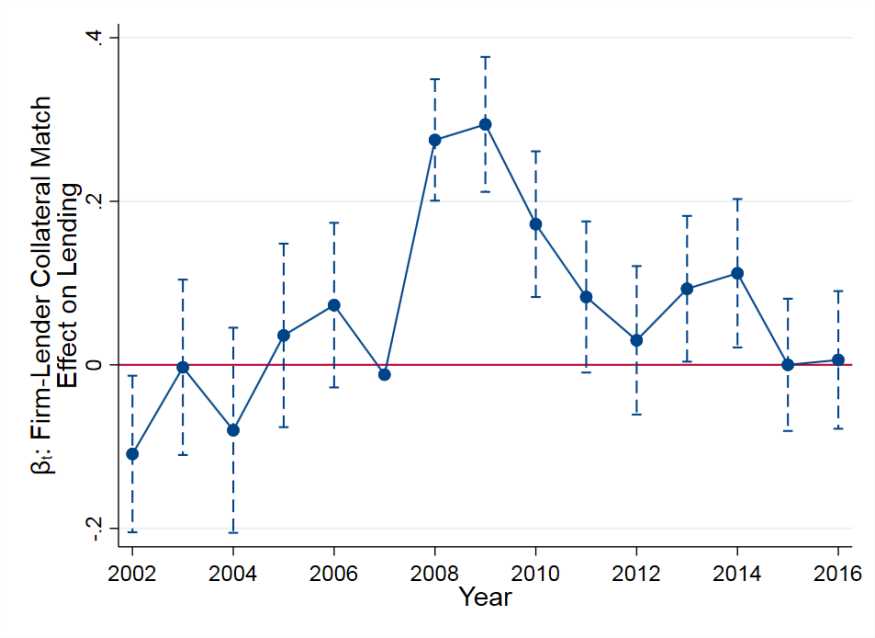


Figure 5: Distribution of Firm-Lender Collateral Match Quality - Post-Crisis Matches

This figure plots the kernel density for Firm-Lender Collateral Match Quality. Firm-Lender Collateral Match Quality captures the level of collateral specialization of the lender in the borrower's collateral, based on pre-crisis (2002-07) loans. Values are capped at 5th and 95th percentiles. The solid line includes all potential firm-lender pairs in Texas based on the total set of borrowers and lenders in the sample. The dashed line plots the distribution of scores for firm-lender pairs with a match in the post-crisis (2008-16) period.

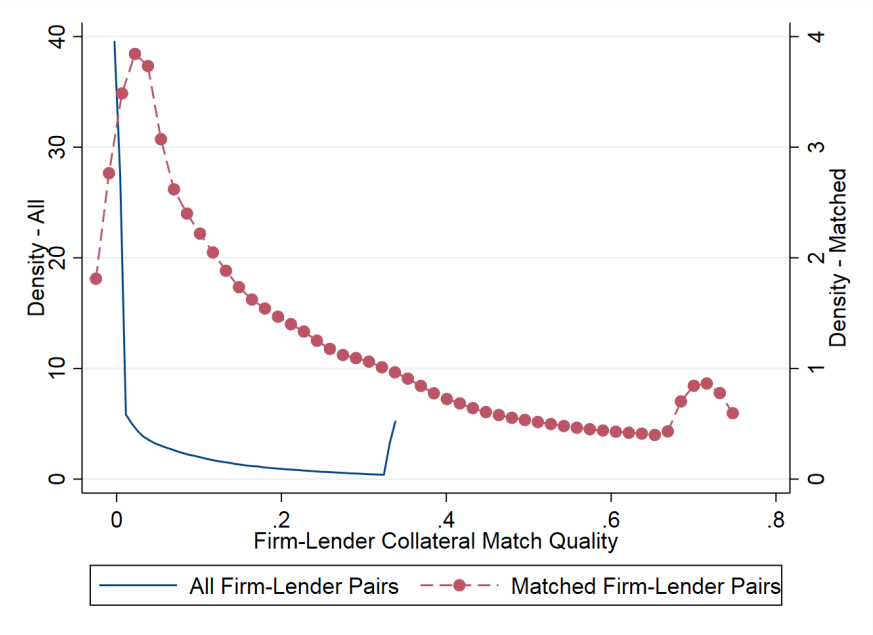


Figure 6: Low Bank Capitalization Does Not Explain Lending Change

This figure examines the interaction between lender specialization and bank capitalization on access to credit around the 2008 financial crisis. The sample consists of borrower-lender pairs in Texas with a lending relationship between 2002-07. Sample is restricted to loans made by banks (commercial bank, nonbank-subsidiary of bank holding company, or a credit union). Regression betas from the following specification are plotted:

$$\begin{aligned}\mathbf{y}_{flt} =& \alpha_{fl} + \delta_t + \beta_{1t} \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t + \\ & \beta_{2t} \text{ Firm-Lender Collateral Match}_{fl} \times \mathbf{1}_t \times \text{Low Capital}_l + \epsilon_{fci}\end{aligned}$$

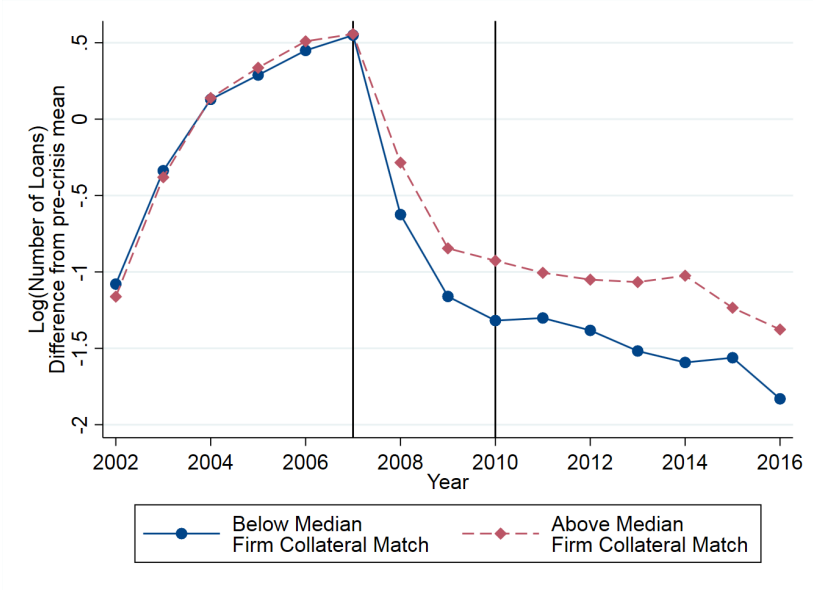
for firm f, lender l and year t. The dependent variable is an indicator that takes value of one if the firm-lender pair is observed to have a loan in a given year, scaled by frequency of loans between the pair in the pre-crisis period. Firm-Lender Collateral Match Quality captures the level of collateral specialization of the lender in the borrower's collateral, and is measured based on pre-crisis (2002-07) loans between the borrower and lender. Low Capital takes a value of 1 for banks with below median Tier-1 Capital Ratio in 2006. Regression includes firm-lender (α_{fl}) and time (δ_t) fixed effects. $\mathbf{1}_t$ takes value 1 in year t and is zero otherwise. Standard errors are clustered at the lender level. Point coefficients and 95% confidence intervals are plotted below. Coefficients can be found in Column 2 of Internet Appendix Table IA4.

Figure 7: Firm Collateral Match on Firm-Level Outcomes

This figure plots examines the effect of borrower-lender collateral match on firm outcomes around the 2008 financial crisis. Sample includes firms in Texas with at least one loan in the pre-crisis (2002-07) period. Firm Collateral Match is the weighted average of firm-lender collateral match quality. Firm collateral match captures the average level of collateral specialization of relationship lenders of the borrower. Higher values indicate the firm borrows from lenders with greater specialization in the borrower's collateral.

(a) **Lending**

Log of the number of loans originated in a given year demeaned by the average pre-crisis (2002-07) log number of loans is plotted.



(b) **Firm Employment**

Average of scaled firm-level employment is plotted. Scaled Employment is annual firm employment scaled by pre-crisis (2002-07) level of firm employment.

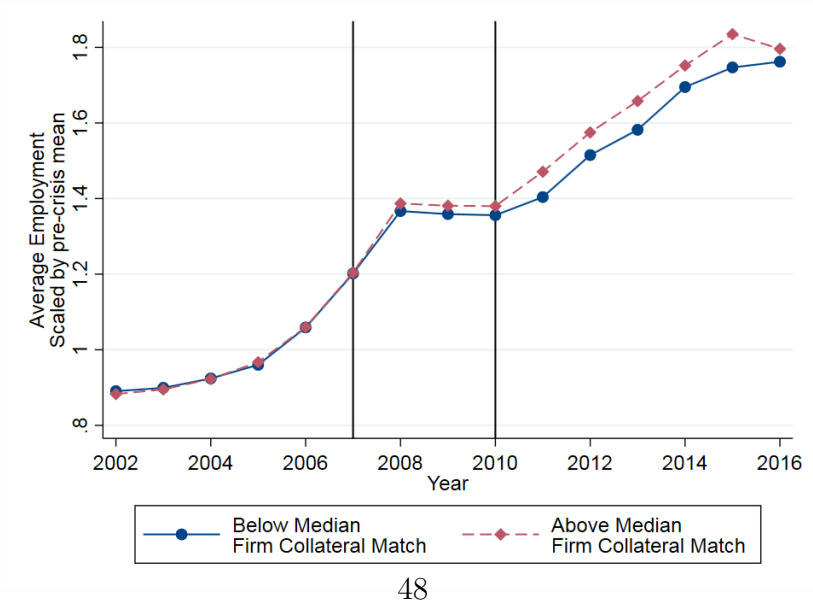
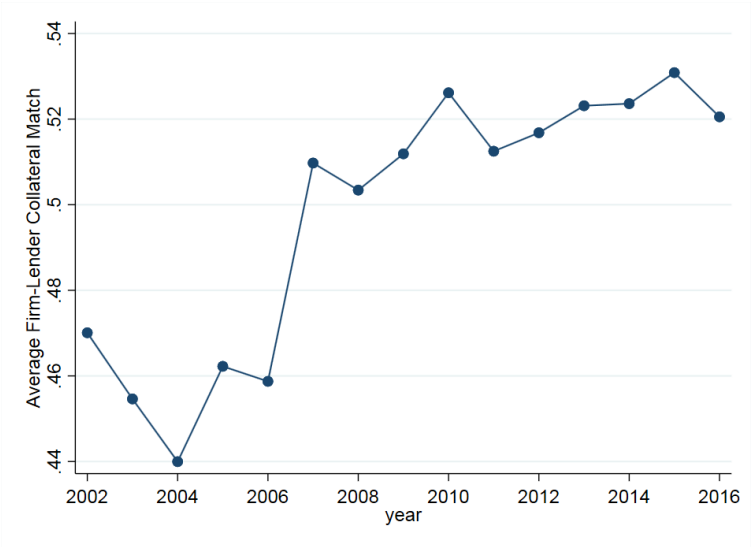


Figure 8: Aggregate Trends

This figure examines the time-varying effect of lender collateral specialization on credit access around the 2008 financial crisis. Firm-lender collateral match quality captures the level of collateral specialization of the lender in borrower's collateral and is calculated based on all loans in the sample between 2002 and 2016.

(a) **Average Firm-Lender Collateral Match Quality**

This figure plots the average level of Firm-Lender Collateral Match Quality over time for firm-lender pairs with a loan in the given year.

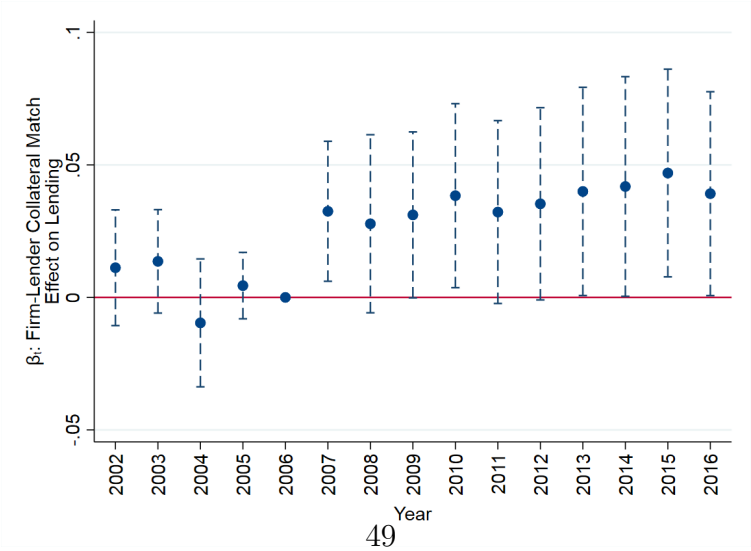


(b) **Dynamic Difference-in-Difference**

This figure plots the coefficients from the following regression:

$$\mathbf{y}_{flt} = \alpha_{fl} + \delta_t + \beta_t \text{Firm-Lender Collateral Match}_{fl} + \epsilon_{flt}$$

Dependent variable takes value of one if the firm f gets a loan from lender l in year t and zero otherwise. The sample includes all firm-lender pairs with at least one loan between 2002-16. 2006 is the omitted year. Standard errors are clustered at the lender level. Point coefficients and 95% confidence intervals are plotted below.



Tables

Table 1: Summary Statistics

Panel A - Firm-Lender Level Variables

This table shows summary statistics for variables at the firm-lender level. Sample includes firm-lender pairs with at least one loan in the pre-crisis (2002-07) period. Multi-relationship firms include firms with more than one lending relationship in the pre-crisis (2002-07) period. The unit of observation is a firm-lender pair. Repeat loan takes a value of one if the firm gets a loan between 2008-16 from the same lender and zero otherwise. Industry shares at the 2,4,6 digit are calculated as the pre-crisis (2002-07) share of the industry in the lender's portfolio. Lender share is the share of lending from the lender in the borrower's portolfio. Avg. number of past loans is the average annual number of loans between the borrower and lender in the pre-crisis period. Time from last loan is the number of years since the last loan between the borrower-lender pair and 2007. Bank takes a value of one if the lender is a commercial bank, nonbank subsidiary of bank holding company, or a credit union and zero otherwise. Top 4 takes a value of one if the lender is one of the large four commercial banks - JPMorgan Chase, Wells Fargo, Bank of America, or Citibank and zero otherwise. Captive takes a value of one if the lender is a captive finance company, i.e., financing arm of a manufacturing company and zero otherwise. Industry performance at 3,4,6-digit NAICS level is measured as the weighted average change in employment at firms in the industry over a three year window around the financial crisis (average 2008-10 level change from 2005-07 level). Scaled Loan takes a value of one if a loan is observed for the firm-lender pair in a given year or zero otherwise, scaled by the frequency of pre-crisis loans between the borrower-lender pair.

	Mean	SD	N
All firms			
Repeat Loan	0.198	0.398	38500
Multi-relationship firms			
Repeat Loan	0.207	0.406	23000
2-digit Industry Share	0.245	0.266	23000
4-digit Industry Share	0.094	0.172	23000
6-digit Industry Share	0.077	0.159	23000
Lender Share	0.339	0.201	23000
Avg. Number of past loans	0.376	0.425	23000
Time from last loan	1.531	1.457	23000
Bank	0.440	0.496	23000
Top4	0.121	0.326	23000
Captive	0.174	0.379	23000
3-digit NAICS performance	-0.299	0.103	23000
4-digit NAICS performance	-0.307	0.134	23000
6-digit NAICS performance	-0.315	0.174	23000
Scaled Loan (Firm-Lender-Year Level)	0.584	1.647	514000

Table 1: Summary Statistics - Contd.

Panel B - Collateral Measures

This table shows summary statistics for measures of collateral specialization at the firm-lender level. Sample includes firms with at least one loan in the pre-crisis (2002-07) period. Firm-Lender Collateral Match Quality captures the level of lender specialization in borrower collateral. It is measured based on a comparison of the firm's collateral to the lending portfolio of the lender based on pre-crisis loans (2002-07). Firm Collateral Match is the firm-level weighted average of firm-lender collateral match quality. Firm Similarity captures the specialization of the average lender in the economy with respect to the borrower's collateral . It is measured based on comparison of the firm's collateral in the pre-crisis period to the (weighted) average lender. Pseudo-percentiles are the average of observations in a ± 1 percentile window around the level of interest.

	Firm-Lender Collateral Match Quality	Firm Collateral Match	Firm Similarity
Mean	0.383	0.382	0.218
Standard Deviation	0.309	0.285	0.153
Pseudo 10th pct (mean of 9 - 11)	0.016	0.030	0.035
Pseudo 25th pct (mean of 24 - 26)	0.094	0.137	0.087
Pseudo 75th pct (mean of 74 - 76)	0.605	0.573	0.318
Pseudo 90th pct (mean of 89 - 91)	0.862	0.808	0.432

Panel C - Firm-Level Variables

This table shows summary statistics for variables at the firm-level. Sample includes firms with at least one loan in the pre-crisis (2002-07) period. Repeat loan takes a value of one if firm gets a repeat loan from any of its relationship lenders in the post-crisis period and zero otherwise. New Loan takes a value of one if firm gets any loan in the post-crisis period, irrespective of whether the firm and lender had a pre-crisis relationship and zero otherwise. New Lender takes a value of one if the firm gets at least one loan from a lender it did not borrow from in the pre-crisis period and zero otherwise. Firm Age is the log of the number of years the firm has been in operation as of 2007. Firm Size is the log of employment at the firm in 2007. Average employment change is symmetric growth rate of firm employment between the pre-crisis and post-crisis periods and is bounded between [-2,2]. Scaled Employment is annual firm employment scaled by pre-crisis level of firm employment.

	Mean	SD	N
Repeat Loan	0.308	0.462	23500
New Loan - Total	0.616	0.486	23500
New Lender	0.524	0.499	23500
Firm Age (2007)	12.73	9.901	23500
Firm Size (2007)	2.648	1.513	23500
Average Employment Change (2002-07 to 2008-16)	0.066	0.650	23500
Average Scaled Employment (Firm-Year Level)	1.098	0.832	303000

Table 2: Lender Collateral Specialization and Lending

This table studies the effect of borrower-lender collateral match on access to credit in the aftermath of the 2008 financial crisis. The sample consists of borrower-lender pairs in Texas with a lending relationship between 2002-07. The unit of observation is a firm-lender pair. Regression specification is as follows:

$$\text{Repeat Loan}_{fl} = \alpha_f + \gamma_l + \beta \text{ Firm-Lender Collateral Match Quality}_{fl} + \epsilon_{fl}$$

for firm f and lender l. The dependent variable takes a value of one if the firm gets a new loan between 2008 and 2016 from the same lender and zero otherwise. Firm-Lender Collateral Match Quality captures the level of collateral specialization of the lender in the borrower's collateral. It is created by comparing the collateral pledged by the borrower to the collateral portfolio of the lender based on pre-crisis (2002-07) loans. Higher values of the measure implies the lender has a greater specialziation in the collateral of the borrower. Regression includes firm and lender fixed effects. The firm controls are firm size measured by employment, and firm age in 2007. Standard errors are clustered at lender level.
Columns 1-4 include the full sample of firms. Columns 5-7 are restricted to firms with multiple lending relationships.

	All Firms				Multi-Relationship Firms		
	(1) Loan	(2) Loan	(3) Loan	(4) Loan	(5) Loan	(6) Loan	(7) Loan
Firm-Lender Collateral Match Quality	0.066*	0.078**	0.083**	0.082***	0.109***	0.106***	0.120***
	(0.034)	(0.031)	(0.032)	(0.029)	(0.021)	(0.040)	(0.022)
Observations	38500	38500	38500	38500	23000	23000	23000
County x Industry FE	N	Y	N	Y	Y	N	N
Lender FE	N	N	Y	Y	Y	N	Y
Firm Controls	N	N	N	Y	Y	N	N
Firm FE	N	N	N	N	N	Y	Y
R^2	0.003	0.077	0.158	0.215	0.265	0.388	0.528

Table 3: Collateral vs. Industry Specialization

This table examines the impact of lender collateral specialization on credit access in the aftermath of the 2008 financial crisis, after controlling for the lender's industry specialization. The sample consists of borrower-lender pairs in Texas with a lending relationship between 2002-07. The unit of observation is a firm-lender pair. The dependent variable takes a value of one if the firm gets a new loan between 2008 and 2016 from the same lender and zero otherwise. Firm-Lender Collateral Match Quality captures the level of collateral specialization of the lender in the borrower's collateral. Industry shares at the 2,4,6 digit are calculated as the pre-crisis (2002-07) share of the industry in the lender's portfolio. Standard errors are clustered at lender level.

Panel A - Inclusion of Lender-Industry fixed effects

	(1) Loan	(2) Loan	(3) Loan
Firm-Lender Collateral Match Quality	0.120***	0.132***	0.134***
	(0.022)	(0.026)	(0.027)
Observations	23000	23000	23000
Firm FE	Y	Y	Y
Lender FE	Y	N	N
Lender x 2-digit NAICS FE	N	Y	N
Lender x 3-digit NAICS FE	N	N	Y
R^2	0.528	0.643	0.703

Panel B - Inclusion of Lender-Industry Shares

	(1) Loan	(2) Loan	(3) Loan
Firm-Lender Collateral Match Quality	0.115***	0.114***	0.114***
	(0.022)	(0.022)	(0.022)
2-digit Industry Share	0.118***		
	(0.029)		
4-digit Industry Share		0.217***	
		(0.047)	
6-digit Industry Share			0.233***
			(0.045)
Observations	23000	23000	23000
Firm FE	Y	Y	Y
Lender FE	Y	Y	Y
R^2	0.529	0.529	0.529

Table 4: Collateral Specialization vs. Soft Information

This table examines the impact of lender collateral specialization on credit access in the aftermath of the 2008 financial crisis, after controlling for potential soft information. The sample consists of borrower-lender pairs in Texas with a lending relationship between 2002-07. The unit of observation is a firm-lender pair. The dependent variable takes a value of one if the firm gets a new loan between 2008 and 2016 from the same lender and zero otherwise. Firm-Lender Collateral Match Quality captures the level of collateral specialization of the lender in the borrower's collateral. Controls include the average annual number of pre-crisis loans between the borrower and lender, the lender's share in total lending to the borrower in the pre-crisis period, the number of years between 2007 and the last pre-crisis (2002-07) loan between the borrower and lender. Standard errors are clustered at lender level.

	(1) Loan	(2) Loan	(3) Loan	(4) Loan	(5) Loan
Firm-Lender Collateral Match Quality	0.120***	0.074***	0.068***	0.100***	0.068***
	(0.022)	(0.018)	(0.018)	(0.020)	(0.017)
Lender Share		0.405***			0.323***
		(0.028)			(0.027)
Avg. Number of past loans			0.186***		
			(0.011)		
Time From Last Loan				-0.052***	-0.041***
				(0.004)	(0.004)
Observations	23000	23000	23000	23000	23000
Firm FE	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y
R^2	0.528	0.542	0.544	0.541	0.549

Table 5: Heterogeneous Treatment Effect

This table examines variation across lender types in the impact of collateral specialization on credit access in the aftermath of the 2008 financial crisis. The sample consists of borrower-lender pairs in Texas with a lending relationship between 2002-07. The unit of observation is a firm-lender pair. The dependent variable takes a value of one if the firm gets a new loan between 2008 and 2016 from the same lender and zero otherwise. Firm-Lender Collateral Match Quality captures the level of collateral specialization of the lender in the borrower's collateral. Bank is an indicator that takes a value of one if the lender is a commercial bank, nonbank-subsidiary of bank holding company, or a credit union. Top4 is an indicator that takes a value of one for the 4 largest commercial banks by size - JP Morgan Chase, Bank of America, Wells Fargo, or Citibank including acquisitions. Captive Finance is an indicator that takes a value of one if the parent company of the lender is a manufacturing company. Standard errors are clustered at lender level.

	(1) Loan	(2) Loan	(3) Loan
Firm-Lender Collateral Match	0.129***	0.125***	0.091***
	(0.030)	(0.024)	(0.020)
Firm-Lender Collateral Match × Bank	-0.022		
	(0.039)		
Firm-Lender Collateral Match × Captive Finance		0.205***	
		(0.046)	
Firm-Lender Collateral Match × Top4			-0.039
			(0.051)
Observations	23000	23000	23000
Firm FE	Y	Y	Y
Lender FE	Y	Y	Y
R^2	0.528	0.528	0.529

Table 6: Aggregate Effects - Counter-factual Exercise

This table presents the aggregate effect on lending under counterfactual firm-lender matching exercises. Sample is restricted to firm-lender pairs with a loan between 2002-07.
Counter-factual excercise calculates change in lending on adjusting firm-lender collateral match quality from current level to counter-factual levels keeping all else about the firm-lender pair the same. Results presented as percentage increase in lending over current level of lending.
For each firm-lender pair, I take as given the collateral plegded between the pair. Given the collateral, I estimate hypothetical collateral match scores to all lenders in the sample. The highest score is assigned as the value for Best Available Match for Collateral.
Next, I consider improvement in lending under hypothetical scenario where specialized lenders exist for all borrowers. I take the 90th percentile, the 95th percentile, and highest firm-lender collateral match score from the full distribution of match scores. Lending to the borrower is estimated under the hypothetical scenario where a specialzied lender for the borrower's collateral exists.

Best Available Match for Collateral	14.76%
90th percentile of Firm-Lender Collateral Match	21.76%
95th percentile of Firm-Lender Collateral Match	31.34%
Maximum of Firm-Lender Collateral Match	42.67%

Table 7: Firm-Level Results on Lending

This table examines the effect of collateral match on lending at the firm level. Sample is restricted to firms with a loan between 2002-07. Firm Collateral Match is created as a weighted average of firm-lender collateral match values. Firm-lender collateral match captures the level of collateral specialization of each of the borrower's pre-crisis (2002-07) relationship lenders. Firm Similarity captures the specialization of the average lender in the economy with respect to the borrower's collateral. Firm controls are firm size measured by employment, and firm age in 2007. Standard errors are clustered at the firm level.

Panel A - Relationship Lending

Dependent variable takes a value of one if the firm gets a new loan from any of its relationship lenders after 2008 and zero otherwise. Columns 1-3 include all firms in the sample. Columns 4-6 include firms with multiple lending realtionships pre-crisis (2002-07).

	All Firms			Multi-Relationship Firms		
	(1) Loan	(2) Loan	(3) Loan	(4) Loan	(5) Loan	(6) Loan
Firm Collateral Match	0.062***	0.072***	0.055***	0.125***	0.155***	0.112***
	(0.010)	(0.010)	(0.010)	(0.027)	(0.031)	(0.031)
Observations	23500	23500	23500	7700	7700	7700
County x Industry FE	N	Y	Y	N	Y	Y
Firm Controls	N	N	Y	N	N	Y
R^2	0.001	0.119	0.147	0.003	0.212	0.229

Panel B - New Lender

Dependent variable takes a value of one if the firm gets a loan after 2008 from a lender with no previous relationship and zero otherwise.

	New Lender					
	(1)	(2)	(3)	(4)	(5)	(6)
Firm Similarity	0.285***	0.295***	0.225***	0.311***	0.326***	0.263***
	(0.021)	(0.022)	(0.022)	(0.022)	(0.023)	(0.023)
Firm Collateral Match				-0.047***	-0.054***	-0.067***
				(0.012)	(0.013)	(0.012)
Observations	23500	23500	23500	23500	23500	23500
County x Industry FE	N	Y	Y	N	Y	Y
Firm Controls	N	N	Y	N	N	Y
R^2	0.008	0.105	0.151	0.008	0.106	0.152

Table 8: Firm-Level Results on Employment

This table examines the effect of collateral match on employment at the firm level. Sample is restricted to firms with a loan between 2002-07. Average employment change is symmetric growth rate of firm employment between the pre-crisis and post-crisis periods and is bounded between [-2,2]. Firm Collateral Match is created as a weighted average of firm-lender collateral match values. Firm-lender collateral match captures the level of collateral specialization of each of the borrower's pre-crisis (2002-07) relationship lenders. Repeat Loan takes value if firm gets a loan between 2008 and 2016 from a lender with a pre-crisis relationship. Firm controls are firm size measured by employment, and firm age in 2007. Standard errors are clustered at the firm level.

Panel A - OLS

$$\Delta(\text{Employment})_{fci} = \alpha + \beta_1 \text{Repeat Loan}_f + \beta_3 X_f + \gamma_{ci} + \epsilon_{fci}$$

	(1) $\Delta(Emp)$	(2) $\Delta(Emp)$	(3) $\Delta(Emp)$
Repeat Loan	0.183***	0.188***	0.193***
	(0.009)	(0.010)	(0.009)
Observations	23500	23500	23500
County x Industry FE	N	Y	Y
Firm Controls	N	N	Y
Weighted	N	N	N
R^2	0.017	0.101	0.169

Panel B - IV

$$\text{Repeat Loan}_f = \alpha + \gamma \text{Firm-Collateral Match}_f + X_f + \delta_{ci} + \epsilon_{fci}$$
$$\Delta(\text{Employment})_{fci} = \alpha + \beta \hat{\text{Repeat Loan}}_f + X_f + \delta_{ci} + \epsilon_{fci}$$

	(1) $\Delta(Emp)$	(2) $\Delta(Emp)$	(3) $\Delta(Emp)$
Repeat Loan	0.217***	0.245***	0.258**
	(0.078)	(0.097)	(0.108)
Observations	23500	23500	23500
County x Industry FE	N	Y	Y
Firm Controls	N	N	Y
First Stage F-stat	332.8	221.8	171.8

Appendix A1 Variable Definitions

Table A1: Variable Definitions

Variable Name	Description
Firm-Lender Collateral Match Quality	Captures the level of collateral specialization of a lender in the borrower's collateral. Measured by the Cosine Similarity between collateral pledged by the firm to its relationship lender and collateral of the average borrower of the relationship lender. Similarity based on real assets pledged between 2002-07.
Firm Collateral Match	Captures the average level of collateral specialization of relationship lenders of the borrower. Firm-level average created by averaging firm-lender collateral match of relationship lenders; weighted by share of lending to the borrower by each lender. $\sum_l \text{Firm-Lender Collateral Match Quality}_{fl} \times w_{fl}$
Firm Similarity	Captures the specialization of the average lender in the economy with respect to the borrower's collateral. Measured as the Cosine Similarity between collateral pledged by the firm and the average borrower in the economy; based on real assets pledged between 2002 and 2007
Repeat Loan	Variable that takes value 1 if firm receives a loan in the post-crisis period (2008-16) from a lender with a relationship in the pre-crisis (2002-07) period
New Loan	Variable that takes value 1 if firm receives a loan in the post-crisis period (2008-16)
New Lender	Variable that takes value 1 if firm receives a loan in the post-crisis period (2008-16) from a lender with no pre-crisis relationship
Fraction	Average annual number of loans in the post-crisis period (2008-16) scaled by the average annual number of loans in the pre-crisis period (2002-07)

Table A1: Variable Definitions

Variable Name	**Description**
$\Delta(Emp)$	Average employment change is the symmetric growth rate of firm employment between the pre-crisis(2002-07) and post-crisis (2008-16) periods calculated as, $\Delta(\text{Emp})_f = \frac{\text{Avg. Emp}_{f,2008-16} - \text{Avg. Emp}_{f,2002-07}}{0.5 \times (\text{Avg. Emp}_{f,2008-16} + \text{Avg. Emp}_{f,2002-07})}$
Scaled Employment	Firm employment scaled by the average annual firm employment in the pre-crisis period (2002-07)
Firm County	For single-establishment firms - county of operation; for multi-establishment firms - county with highest employment share of the firm
Firm Industry	For single-establishment firms - industry of operation; for multi-establishment firms - industry with highest employment share of the firm; 2-digit NAICS in baseline specification
Firm Size	Log(Employment+1) based on 2007 employment of the firm
Firm Age	Log(Firm-Age+1) based on 2007 age of the firm

Appendix A2 Additional Figures

Figure A1: Sample UCC Filing

[redacted]

File Number: 20140076446F
Date Filed: 8/12/2014 10:14:00 AM
Elaine F. Marshall
NC Secretary of State

UCC FINANCING STATEMENT
FOLLOW INSTRUCTIONS

A. NAME & PHONE OF CONTACT AT FILER (optional)
Gisella Melendez
B. E-MAIL CONTACT AT FILER (optional)
efiling@wolterskluwer.com
C. SEND ACKNOWLEDGMENT TO: (Name and Address)
CT Lien Solutions
P.O. Box 29071
Glendale, CA 91209-9071

THE ABOVE SPACE IS FOR FILING OFFICE USE ONLY

1. DEBTOR'S NAME: Provide only one Debtor name (1a or 1b) (use exact, full name; do not omit, modify, or abbreviate any part of the Debtor's name); if any part of the Individual Debtor's name will not fit in line 1b, leave all of item 1 blank, check here ☐ and provide the Individual Debtor information in item 10 of the Financing Statement Addendum (Form UCC1Ad)

1a. ORGANIZATION'S NAME: Best Dedicated, LLC					
OR 1b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NAME	ADDITIONAL NAME(S)/INITIAL(S)		SUFFIX	
1c. MAILING ADDRESS: 829 Graves Street	CITY: Kernersville	STATE: NC	POSTAL CODE: 28269	COUNTRY: USA	

2. DEBTOR'S NAME: Provide only one Debtor name (2a or 2b) (use exact, full name; do not omit, modify, or abbreviate any part of the Debtor's name); if any part of the Individual Debtor's name will not fit in line 2b, leave all of item 2 blank, check here ☐ and provide the Individual Debtor information in item 10 of the Financing Statement Addendum (Form UCC1Ad)

2a. ORGANIZATION'S NAME					
OR 2b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NAME	ADDITIONAL NAME(S)/INITIAL(S)		SUFFIX	
2c. MAILING ADDRESS	CITY	STATE	POSTAL CODE	COUNTRY	

3. SECURED PARTY'S NAME (or NAME of ASSIGNEE of ASSIGNOR SECURED PARTY): Provide only one Secured Party name (3a or 3b)

3a. ORGANIZATION'S NAME: Webster Capital Finance, Inc.					
OR 3b. INDIVIDUAL'S SURNAME	FIRST PERSONAL NAME	ADDITIONAL NAME(S)/INITIAL(S)		SUFFIX	
3c. MAILING ADDRESS: 344 Main Street	CITY: Kensington	STATE: CT	POSTAL CODE: 06037	COUNTRY: USA	

4. COLLATERAL: This financing statement covers the following collateral:

One (1) 2015 Transcraft Combo 48 x 102 Flatbed Trailer, VIN: 1TTF482C5F3843255
One (1) 2015 Transcraft Combo 48 x 102 Flatbed Trailer, VIN: 1TTF482C7F3843256
One (1) 2015 Transcraft Combo 48 x 102 Flatbed Trailer, VIN: 1TTF482C9F3843257
One (1) 2015 Transcraft Combo 48 x 102 Flatbed Trailer, VIN: 1TTF482C3F3843254
financed by Secured Party from time to time, all replacements, accessories, accessions, attachments, returned or repossessed inventory and proceeds thereof including without limitation, cash, accounts, receivables, notes, rental contract rights, chattel paper, documents of title, general intangibles, trade-ins, insurance proceeds, any other obligation due or to become due to the Debtor for payments for any of the described inventory.
#68730-05

5. Check only if applicable and check only one box: Collateral is ☐ held in a Trust (see UCC1Ad, item 17 and Instructions) ☐ being administered by a Decedent's Personal Representative

6a. Check only if applicable and check only one box: ☐ Public-Finance Transaction ☐ Manufactured-Home Transaction ☐ A Debtor is a Transmitting Utility

6b. Check only if applicable and check only one box: ☐ Agricultural Lien ☐ Non-UCC Filing

7. ALTERNATIVE DESIGNATION (if applicable): ☐ Lessee/Lessor ☐ Consignee/Consignor ☐ Seller/Buyer ☐ Bailee/Bailor ☐ Licensee/Licensor

8. OPTIONAL FILER REFERENCE DATA:
NC-0-44455274-48900822

FILING OFFICE COPY — UCC FINANCING STATEMENT (Form UCC1) (Rev. 04/20/11)

Figure A2: Time Varying Effect of Firm Collateral Match on Lending

This figure examines the time-varying effect of collateral match on access to credit around the 2008 financial crisis. The sample consists of borrowers in Texas with a lending relationship between 2002-07. Observations are at the firm-year level. Regression betas from the following specification are plotted:

$$\mathbf{y}_{ft} = \alpha_f + \gamma_t + \beta_t \text{ Firm Collateral Match}_f \times \mathbf{1}_t + \epsilon_{ft}$$

for firm f, and year t. The dependent variable is an indicator that takes value of one if the firm is observed to have a loan in a given year, scaled by frequency of loans to the firm in the pre-crisis period. Firm Collateral Match is created as a weighted average of firm-lender collateral match values. Firm-lender collateral match captures the level of collateral specialization of each of the borrower's pre-crisis (2002-07) relationship lenders. Regression includes firm (α_f) and year (γ_t) fixed effects. $\mathbf{1}_t$ takes value 1 in year t and is zero otherwise. Standard errors are clustered at the firm level. Point coefficients and 95% confidence intervals are plotted. Coefficients can be found in column 2 of Table IA2 and Table IA3.

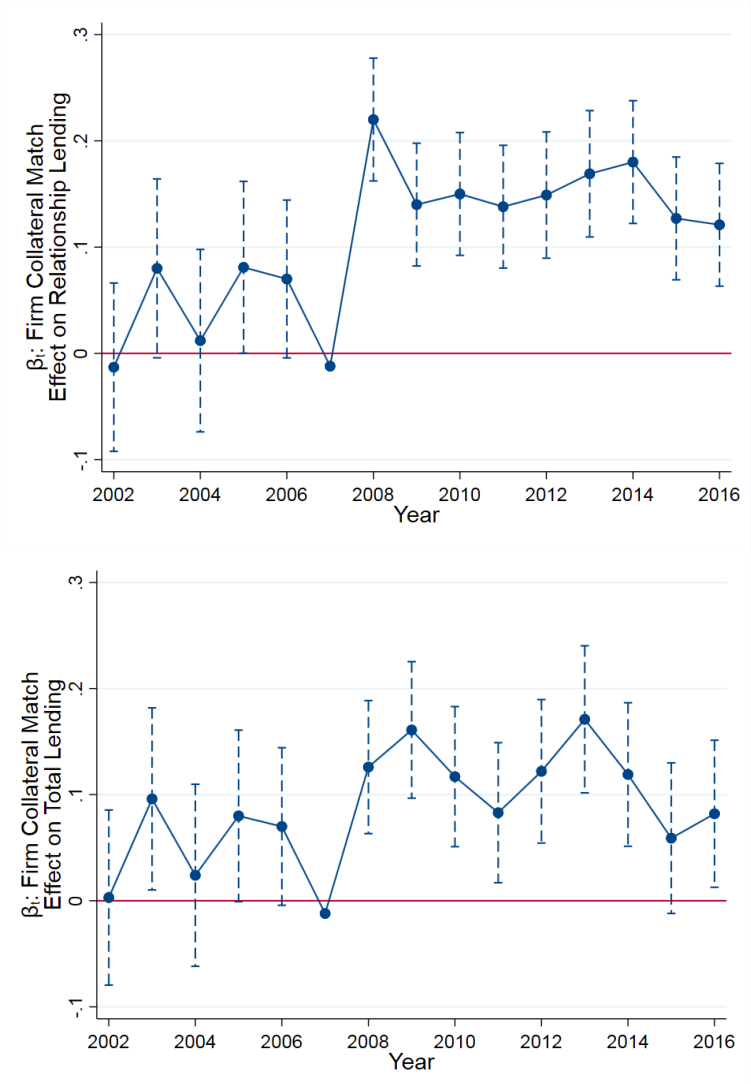


Figure A3: Regression Betas

Coefficients from the following regression specification are plotted -

$$\text{Scaled Employment}_{ft} = \alpha + \text{Firm Similarity}_f \times \mathbf{1}_t + \delta_t + \epsilon_{ft}$$

for firm f, in year t where Scaled Employment is annual firm employment scaled by average pre-crisis level of employment at the firm. Firm Similarity is a measure of collateral match between the borrower and (weighted) average of all lenders in the sample based on pre-crisis (2002-07) collateral plegded by firms. $\mathbf{1}_t$ takes value 1 in year t and is zero otherwise. Regression includes time fixed effects (δ_t). Regression is weighted by the firm employment in 2007.

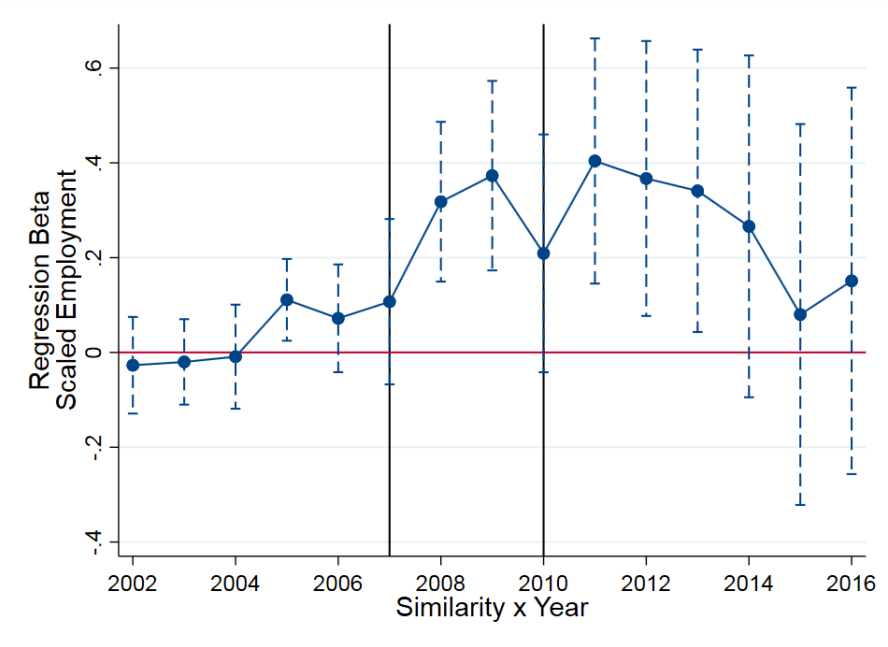
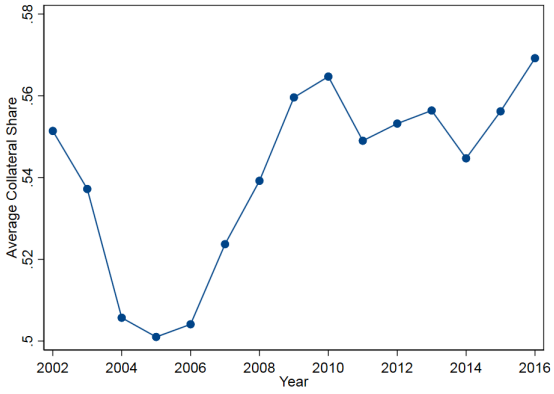
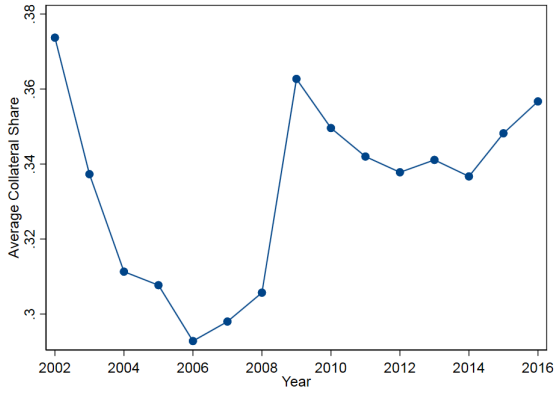


Figure A4: Lender Specialization

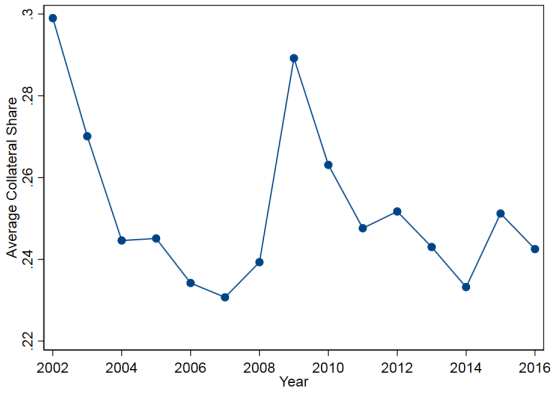
This figure plots average share of top 6 types of collateral in the lender's portfolio over time. For each lender, collateral types are ranked based on their share in the lender's portfolio between 2002 and 2007. Collateral shares by rank are averaged across lenders in each year.



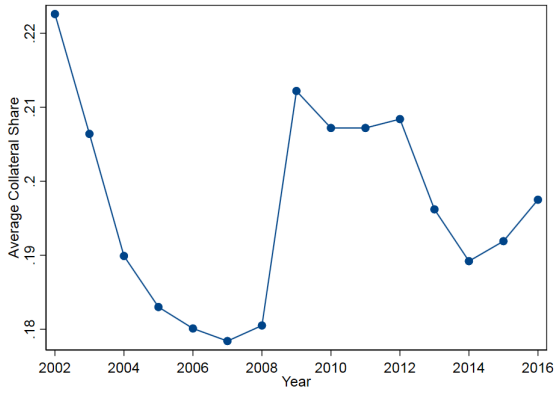
(a) Rank 1



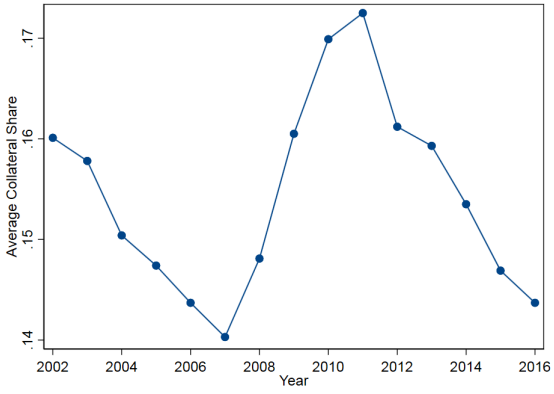
(b) Rank 2



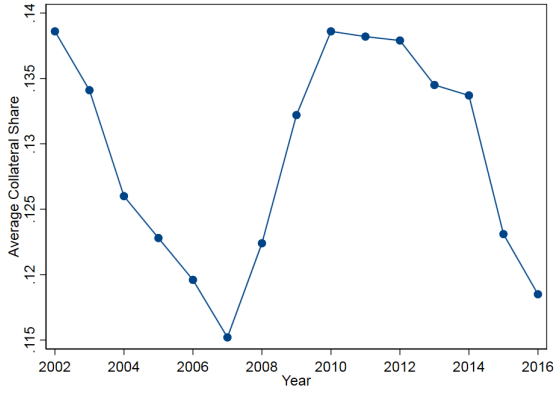
(c) Rank 3



(d) Rank 4



(e) Rank 5



(f) Rank 6

Appendix A3 Additional Tables

Table A2: Comparison of LBD to Matched Sample

This table compares the firms in the Longitudinal Business Database with an establishment at some point in Texas to the set of matched UCC-LBD firms. Multi-establishment is a value that takes one if the firm has more than a signle establishment.

	All firms	Matched Firms
Firm Employment (2007)	25.03	70.56
Mean Payroll	1061	3421
Multi-Establishment Firms	0.0524	0.08449
Firm Age (2007)	10.66	13.6
No. of Firms	1044000	93000

Table A3: Distribution of Firm Employment

This table provides the distribution of firm employment for the set of UCC firms matched to the LBD

Percentile	Value
Pseudo 10th pct (mean of 9 - 11)	2.157
Pseudo 25th pct (mean of 24 - 26)	5.107
Pseudo 75th pct (mean of 74 - 76)	33.9
Pseudo 90th pct (mean of 89 - 91)	92.01
No. of Firms	23500

Table A4: Comparison of Firm Characteristics by Match Quality

This table provides summary statistics and comparison across groups for firms with above median and below median firm collateral match.

	Mean			
	Below Median	Above Median	Difference	Std. Error
Firm Age	12.47	12.98	-0.5036	0.129
Firm Size	2.552	2.744	-0.1923	0.0197
Multi-Establishment Firm	0.0798	0.1015	-0.0218	0.0037
Multi-Relationship Firm	0.2975	0.3583	-0.0609	0.0061
Avg annual number loans (2002-07)	0.6003	0.8005	-0.2003	0.0142
Avg annual number loans (2008-16)	0.1153	0.2066	-0.0913	0.0072
Exit Rate	0.3692	0.353	0.0162	0.0063

Table A5: Largest Lenders in the Sample

This table includes the 40 largest lenders in Texas including the number of loans originated by the lender between 2002 and 2016.

Lender Name	No. of Loans
Wells Fargo	38736
John Deere	38602
JPMorgan Chase	33233
Caterpillar	24181
US Bancorp	18840
GE Capital	15089
Dell Financial Services	11876
Citibank	11254
Bank Of America	9667
The Frost National Bank	9664
Toyota Motor Credit Corp	8608
CNH Capital America	8156
Compass Bank	7816
TCF National Bank	7766
Kubota	7512
Plainscapital Bank	6960
De Lage Landen	6419
Texas Capital Bank	6200
Holt Cat	5971
Bank Of The West	5827
Automotive Finance Corporation	5809
Prosperity Bank	5779
Amegy Bank	5574
Frost Bank	5505
Komatsu Financial Limited Partnership	5168
First National Bank	5008
ISI Commercial Refrigeration	4770
First Financial Bank	4535
CIT Finance	4368
First State Bank	4325
Sterling Bank	3982
Regions Bank	3886
Bank Of Texas	3642
Texas State Bank	3516
RDO Equipment Co	3346
Nextgear Capital Inc	3286
The American National Bank Of Texas	3191
HPSC Inc	3182
Austin Bank Texas	3099
City Bank	3055

Table A6: Interaction with Balance Sheet Variables

This table studies the effect of lender health and borrower-lender collateral match on access to credit in the aftermath of the 2008 financial crisis. The sample consists of borrower-lender pairs in Texas with a lending relationship between 2002-07. The dependent variable is an indicator that takes value of one if the firm-lender pair is observed to have a loan in a given year, scaled by frequency of loans between the pair in the pre-crisis period. Firm-Lender Collateral Match Quality captures the level of collateral specialization of the lender in the borrower's collateral. Loan Loss Provision is the amount expensed as provisions for credit losses in the previous year scaled by bank assets. Loan Loss Rate is the previous year allowance for loan and lease losses scaled by the bank assets. Loan Chargeoff Rate is the ratio of charge-offs on commercial and industrial loans (C&I) by the volume of C&I lending in the pervious year. Post is an indicator that takes a value of one for years after 2007. Sample is restricted to banks. Standard errors clustered at lender level.

	(1) Scaled Loan	(2) Scaled Loan	(3) Scaled Loan	(4) Scaled Loan
Firm-Lender Collateral Match	0.341***	0.275***	0.337***	0.227***
x Post	(0.088)	(0.038)	(0.043)	(0.033)
Firm-Lender Collateral Match	-1.699***			
x Tier-1 Risk Based Capital$_{t-1}$	(0.658)			
Firm-Lender Collateral Match	-0.596			
x Tier-1 Risk Based Capital$_{t-1}$ x Post	(0.503)			
Firm-Lender Collateral Match		-1.158***		
x Loan Loss Provision$_{t-1}$		(0.330)		
Firm-Lender Collateral Match		1.161***		
x Loan Loss Provision$_{t-1}$ x Post		(0.329)		
Firm-Lender Collateral Match			-2.200***	
x Loan Loss Rate$_{t-1}$			(0.527)	
Firm-Lender Collateral Match			2.191***	
x Loan Loss Rate$_{t-1}$ x Post			(0.525)	
Firm-Lender Collateral Match				-0.142***
x Loan Chargeoff Rate$_{t-1}$				(0.028)
Firm-Lender Collateral Match				0.051**
x Loan Chargeoff Rate$_{t-1}$ x Post				(0.022)
Observations	249000	249000	249000	249000
Lender x Year FE	Y	Y	Y	Y
Firm x Lender FE	Y	Y	Y	Y
R^2	0.239	0.239	0.239	0.239

Table A7: Firm-Level Results on Employment

This table examines the effect of collateral match on employment at the firm level. Sample is restricted to firms with a loan between 2002-07. Average employment change is symmetric growth rate of firm employment between the pre-crisis and post-crisis periods and is bounded between [-2,2]. New Loan takes value if firm gets a loan between 2008 and 2016 from any lender. Firm Collateral Match is created as a weighted average of firm-lender collateral match values. Firm-lender collateral match captures the level of collateral specialization of each of the borrower's pre-crisis (2002-07) relationship lenders. Firm Similarity is a measure of collateral match between the borrower and (weighted) average of all lenders in the sample based on pre-crisis (2002-07) collateral plegded by firms. Firm controls are firm size measured by employment, and firm age in 2007. Standard errors are clustered at firm level.

Panel A - OLS

$$\Delta(\text{Employment})_{fci} = \alpha + \beta_1 \text{New Loan}_f + \beta_3 X_f + \gamma_{ci} + \epsilon_{fci}$$

	(1) $\Delta(Emp)$	(2) $\Delta(Emp)$	(3) $\Delta(Emp)$	(4) $\Delta(Emp)$
New Loan	0.240***	0.243***	0.256***	0.272***
	(0.009)	(0.009)	(0.009)	(0.038)
Observations	23500	23500	23500	23500
County x Industry FE	N	Y	Y	Y
Firm Controls	N	N	Y	Y
Weighted	N	N	N	Y
R^2	0.032	0.115	0.184	0.358

Panel B - IV

$$\text{New Loan}_f = \alpha + \beta_1 \text{Firm-Similarity}_f + \beta_1 \text{Firm-Collateral Match}_f + X_f + \delta_{ci} + \epsilon_{fci}$$

$$\Delta(\text{Employment})_{fci} = \alpha + \beta \hat{\text{New Loan}}_f + X_f + \delta_{ci} + \epsilon_{fci}$$

	(1) $\Delta(Emp)$	(2) $\Delta(Emp)$	(3) $\Delta(Emp)$	(4) $\Delta(Emp)$
New Loan	0.319***	0.338***	0.193**	0.934***
	(0.072)	(0.079)	(0.093)	(0.267)
Observations	23500	23500	23500	23500
County x Industry FE	N	Y	Y	Y
Firm Controls	N	N	Y	Y
Weighted	N	N	N	Y
First Stage F-stat	181.2	152.8	106.8	13.95